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HOME ENERGY MANAGEMENT SYSTEM: A MULTI-OBJECTIVE OPTIMIZATION MODEL FOR SCHEDULING LOADS

JACLASON MACHADO VERAS

ADVISOR: PROF. DR. PLÁCIDO ROGÉRIO PINHEIRO
CO-ADVISOR: PROF. DR. RICARDO DE ANDRADE LIRA RABÊLO

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Thesis presented to the Graduate Program in Applied Informatics of the University of Fortaleza in partial fulfilment of the requirements for the degree of Doctor in Applied Informatics.

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Banca Examinadora:

Prof. Plácido Rogério Pinheiro, D.Sc.
(Orientador – UNIFOR)

Prof. Ricardo de Andrade Lira Rabêlo, D.Sc.
(Coorientador – UFPI)

Prof. Raimir Holanda Filho, D.Sc.
(Membro – UNIFOR)

Prof. Joel José Puga Coelho Rodrigues, D.Sc.
(Membro – INATEL/IT)

Prof. Otacílio da Mota Almeida, D.Sc.
(Membro – UFPI)

Prof. João Xavier da Cruz Neto, D.Sc.
(Membro – UFPI)

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in his unreasonable loyalty
moreover, silent understanding.

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"There is a driving force more powerful than steam, electricity and nuclear power: the will."

Albert Einstein

Abstract

Demand Response (DR) aims to motivate end consumers to change their energy consumption patterns in response to changes in electricity prices or when the reliability of the electrical power system (EPS) is compromised. Most of the recent studies show that the main goal is to minimize the cost associated with the consumption of electric energy without considering the preferences/needs of end consumers. Therefore, it is possible to state that these works do not consider the real difficulty of the problem which involves scheduling the use of home appliances and they do not evaluate aspects such as: (a) different residential scenarios; (b) various categories of home appliances; (c) the level of satisfaction/comfort of consumers with the new scheduling of their home appliances. Moreover, the studies that dealt with the inconvenience aspect performed simulations without considering the different categories of home appliances, thus reducing the complexity of the method. However, this thesis proposes a home energy management system (HEMS) that aims to schedule the use of each home appliance based on the price of electricity in real-time (RTP) and on the consumer satisfaction/comfort level in order to minimizing the cost associated to the energy consumption, as well as minimizing the inconvenience (dissatisfaction/discomfort) of end consumers ensuring the stability and the safety of the EPS. Therefore, the HEMS through the energy management controller (EMC) determines an optimized timeline for each appliance through the multiobjective DR model validated using Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Language for Interactive General Optimizer (LINGO) and Non-dominated Sorting Genetic Algorithm II (NSGA-II) optimization techniques, and thus ensures a more economic scenario for end consumers. The results show that the HEMS achieved reductions in the cost of electricity for all the Scenarios used while minimally affecting the satisfaction/comfort of the end consumers as well as contemplating all the restrictions.

Keywords: Demand Response; Energy Management; Load Scheduling; Optimization.

Resumo

A Demand Response (DR) visa motivar os consumidores finais a mudar seus padrões de consumo de energia de elétrica em resposta às mudanças nos preços da eletricidade ou quando a confiabilidade do sistema elétrico de potência (EPS) estiver comprometida. A maioria dos estudos recentes mostram que o principal objetivo é minimizar o custo associado ao consumo de energia elétrica sem considerar as preferências/necessidades dos consumidores finais. Portanto, afirmar que esses trabalhos não consideram a real dificuldade do problema que envolve agendar o uso dos aparelhos residenciais e não avaliam aspectos como: (a) diferentes cenários residenciais; (b) várias categorias de aparelhos residenciais; (c) o nível de satisfação/conforto dos consumidores com o novo agendamento de seus aparelhos. Além disso, os estudos que trataram do aspecto da inconveniência realizaram simulações sem levar em conta as diferentes categorias de aparelhos residenciais, reduzindo, assim, a complexidade do método. No entanto, nesta tese propõe-se um sistema de gerenciamento de energia residencial (HEMS) que visa programar o uso de cada aparelho residencial com base no preço da eletricidade em tempo real (RTP) e no nível de satisfação/conforto do consumidor a fim de minimizar o custo associado ao consumo de energia elétrica bem como, minimizar a inconveniência (insatisfação/desconforto) dos consumidores finais, garantindo a estabilidade e a segurança do EPS. Portanto, o HEMS através do controlador de gerenciamento de energia (EMC) determina uma linha do tempo otimizada para cada aparelho por meio do modelo de DR multiobjectivo validado através do uso das técnicas de otimização Algoritmo Genético (GA), Otimização por Enxame de Partículas (PSO), Linguagem para Otimizador Geral Interativo (LINGO) e do Algoritmo Genético de Classificação por Não Dominância II (NSGA-II), garantindo um cenário mais econômico para os consumidores finais. Os resultados mostram que o HEMS alcançou reduções no custo da eletricidade para todos os cenários utilizados, afetando minimamente a satisfação/conforto dos consumidores finais, bem como, levando em conta todas as restrições.

Palavras-Chave: Resposta à Demanda; Gerenciamento de Energia; Agendamento de Carga; Otimização.

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List of Abbreviations and Acronyms

AC – Alternating Current

AMI – Advanced Metering Infrastructure

BESS – Battery Energy Storage System

CPP – Critical-Peak Pricing

DC – Direct Current

DER – Distributed Energy Resource

DP – Dynamic Programming

DR – Demand Response

DRP – Demand Response Program

DSM – Demand-Side Management

EMC – Energy Management Controller

EMS – Energy Management System

EPS – Electrical Power System

GA – Genetic Algorithm

GSM – Global System for Mobile Communications

HAN – Home Area Network

HEMS – Home Energy Management System

HLC – Home Load Control

HVAC – Heating, Ventilation and Air Conditioning

ICT – Information and Communication Technologies

IoT – Internet of Things

LP – Linear Programming

LPG – Load Profile Generation

LST – Least Slack Time

MCCU – Main Command and Control Unit

MDP – Markov Decision Process

MILP – Mixed-Integer Linear Programming

MINLP – Mixed-Integer Nonlinear Programming

MIP – Mixed-Integer Programming

NAN – Neighborhood Area Network

NFQI – Neural Fitted Q-Iteration

NLP – Nonlinear Programming

NSGA-II – Non-Dominated Sorted Genetic Algorithm

PAR – Peak-to-Average Ratio

PDE – Partial-Differential Equation

PEV – Plug-in Electric Vehicles

PLC – Power Line Communication

PSO – Particle Swarm Optimization

RFID – Radio Frequency Identification

RL – Reinforcement Learning

RTP – Real-Time Pricing

SG – Smart Grid

SM – Smart Meter

SVM – Support Vector Machine

TOU – Time-Of-Use

WAN – Wide Area Network

CONTENTS

Chapter 1

INTRODUCTION

This chapter first presents the issues that motivated this thesis, and then defines the problem, gives a general view of the proposal, its objectives, justification, as well as the main contributions and the organization of this work.

1.1 Context and Motivation

The growth of the global population has caused an increase in the complexity of the electricity supply. Therefore, there is a need for studies and research concerning the quality and reliability of electric power systems in order to prevent interruptions in the supply of electricity and reduce price increases, among other problems (ALTHAHER; MANCARELLA; MUTALE, 2015; DAI *et al.*, 2017; LI *et al.*, 2015; SOU *et al.*, 2011). At the same time, the pressure on natural resources worldwide and concern for the environment is also increasing rapidly. One of the solutions to help overcome such problems is to use a smart grid (SG). An SG is a system that applies information and communication technologies (ICT) to improve the interaction among all the devices of an electrical power system (EPS) and its consumers (ZHAO *et al.*, 2013). This interaction can be used by end consumers to improve their electricity consumption pattern in order to reduce the cost of electricity.

The authors in (DENG *et al.*, 2015; FANG *et al.*, 2012) state that SG represents a major change in the electric sector and it was conceived to improve the generation, transmission, distribution and consumption of electricity. In the generation process, SG is able to control failures and oscillations arising from the energy production coming from renewable sources and to handle the decrease or flexibilization of the use of thermoelectric and other non-renewable sources (IEC, 2010).

In the transmission of loads, SG is used in decision support systems, system integrity, protection projects, asset management systems, and condition monitoring devices, and for load distribution SG is involved in automation and distribution protection, distribution management systems and advanced metering infrastructure. In the scope of the end consumers, the SG is used in the electric power management system, in the distributed generation of electric power, in the intelligent homes and the control system and building automation (IEC, 2010). Consequently, SG provides significant improvements in the monitoring, management, automation, and quality of electricity, which is offered through an electricity network characterized by the intensive use of information and communication technologies (ICTs).

In (PARK *et al.*, 2017), the authors affirm that the demand response control methodologies and smart appliances can optimize the use of electrical resources more efficiently. In this sense, the authors in (MURATORI; SCHUELKE-LEECH; RIZZONI, 2014; OZTURK *et al.*, 2013a; PARVANIA; FOTUHI-FIRUZABAD, 2010) defined a demand response (DR), from the point of view of a smart grid, as a program that provides various incentives and benefits to end consumers to change their electricity consumption patterns in response to changes in the price of electricity over time or when electrical power network reliability is compromised by any EPS overhead. Therefore, the excessive increase in electricity demand has made the use of a DR program interesting for both consumers and the utility (PARVANIA; FOTUHI-FIRUZABAD, 2010; SIANO, 2014).

The most commonly used DR programs (DRPs) are based on price, following one of three tariff models: (1) Time-of-Use (TOU), which offers consumers different electric energy tariffs during different periods of the day (SHAO *et al.*, 2010; WANG *et al.*, 2013b) and is generally based on the average cost of generation and delivery of energy over a 24-h period (FARIA; VALE, 2011); (2) Real-Time Pricing (RTP), when the price of electricity is modified hourly throughout the day, and this may reflect the cost for generation or the wholesale price level; and finally, (3) Critical-Peak Pricing (CPP), which is a dynamic pricing mechanism that uses elements of TOU and RTP to adjust tariffs as a temporary response to events or conditions such as high market prices, or decreasing reserves (WANG *et al.*, 2013b). The authors in (LIN; HU, 2018; ZHAO *et al.*, 2013) affirm that RTP has much greater flexibility than TOU and CPP. Therefore, the increase in the price of the tariff is linked to the increase in demand for electricity or the low energy productivity of the EPS.

Thus, DRPs can be regarded as one of the most important tools for Home Energy Management Systems (HEMS). DRPs are able to interrupt, control, regulate, or curtail the energy of the devices and end consumers have financial support to modify their electricity consumption patterns in order to improve the reliability and efficiency of EPS (HEMMATI; SABOORI, 2017). Moreover, DRPs help the utility companies to shift the load from peak hours to off-peak hours in order to reduce electricity prices as well as to balance the supply and demand (SHAKERI *et al.*, 2018).

The authors in (SETLHAOLO; XIA; ZHANG, 2014) explained that DR has been successful with commercial and industrial consumers due to the ability to significantly reduce the cost associated with the consumption of electricity. However, for the residential setting one of the obstacles to insert a DR program is the need for manual intervention by the consumer in the process of determining the use of residential appliances. Hence, due to a lack of time, and knowledge on the part of the consumer as well as not wanting to participate actively in the programs related to EPS, the implementation of DRs in the residential scenario is affected.

Therefore, **the main motivation of this thesis is to develop a Home Energy Management System (HEMS) that, through its operational core (EMC), aims to program the use of residential appliances considering the real-time pricing of electricity (RTP) as well as the different operating characteristics of home appliances.** The HEMS proposed in this work uses a mathematically formulated DR optimization model as nonlinear programming (NLP) problem in order to (re)schedule the loads to minimize the cost associated with the electricity consumption and the inconvenience level (dissatisfaction/discomfort) of end consumers during the use of the home appliances. Furthermore, the HEMS provides an efficient load management process for balancing the energy supply and demand in order to maximize the reliability and efficiency of EPS.

1.2 Definition of Problem

During the twenty-first century, the demand for electricity increased, exposing various problems in the EPS such as: frailties in electricity distribution at peak times, voltage fluctuations, interruptions in the energy supply and disordered increases in the price of electricity (ALTHAHER; MANCARELLA; MUTALE, 2015; DAI *et al.*, 2017; LI *et al.*, 2015; SOU *et al.*, 2011). Thus, contemporary society, because of its high level of dependence on electricity, began to demand a more reliable and safer energy system (PIPATTANASOMPORN *et al.*, 2012). Hence, the home load management process needs to be planned in a coordinated manner to ensure the efficiency of the electric power system (EPS) and minimize the inconvenience level simultaneously.

Owing to the relevance of DR applicability to the current scenario, which is leading to a possible energy crisis, this issue has been analyzed as a viable alternative in several recent studies (ALTHAHER; MANCARELLA; MUTALE, 2015; NAIR; RAJASEKHAR, 2014; OZTURK *et al.*, 2013b; SAFDARIAN; FOTUHI-FIRUZABAD; LEHTONEN, 2014; VIVEKANANTHAN; MISHRA; LI, 2015; WANG; PARANJAPE, 2017b; XING YAN *et al.*, 2015; ZHAO *et al.*, 2013), discussing and proposing improvements related to the process of load management in smart grids.

In this context, this thesis proposes a home energy management system (HEMS) using a multi-objective DR optimization model mathematically formulated as nonlinear programming (NLP) problem to determine optimal programming of the appliances, considering real-time pricing (RTP) and the different categories of home appliances. **This DR multi-objective optimization model aims to minimize the cost related to the electricity consumption and the inconvenience for the end consumers subjected to a set of restrictions, such as minimum and maximum load limits for each time interval; ramp limits; minimum consumption related to the time horizon; and operational constraints for the different home appliance categories.**

Meanwhile, although the optimization problem is formulated as a nonlinear programming problem, which is difficult to solve in generic terms, different methods using Genetic Algorithm (GA) (LINDEN, 2012; LUCENA, 2013; REY NARIÑO, 2014), LINGO (LINDO SYSTEMS INC., 2016), Particle Swarm Optimization (PSO) (EBERHART; KENNEDY, 1995) and Non-Dominated Sorted Genetic Algorithm (NSGA-II) (DEB *et al.*, 2002) were applied to obtain the optimal solution in mono and multi-objective scenarios, respectively.

1.3 Objectives

The main objective of this work is to develop a home energy management system and a multi-objective DR optimization model to manage the use of residential appliances in order to minimize the cost associated to the electricity consumption and the inconvenience level of the consumers about the operational programming of domestic appliances. Thus, it intends to schedule the use of home appliances considering the changes that occur in the real time pricing of electricity, the restrictions associated with energy consumption (minimum and maximum load limits for each time interval; ramp limits; minimum consumption related to the time horizon) and constraints related to operational aspects for the home appliance categories.

To achieve this general objective, the following specific objectives have been defined:

- To conduct studies on household electricity consumption management, highlighting the aspects related to minimization of electricity cost and inconvenience for consumers on the use of home appliances;
- To develop a DR optimization model to define the optimal programming of residential appliances;
- To apply optimization techniques to solve the DR problem that involves the management of the appliances;
- To analyze the performance of optimization techniques and the impact of different energy consumption profiles concerning the minimization of the cost related to the consumption of electric energy and the inconvenience level of end consumers;
- To evaluate the performance of the results obtained in the computational simulations using statistical metrics in the multi-objective scenario.

1.4 Proposal Overview

This work proposes a home energy management system (HEMS) that aims to program the use of each appliance considering the price of electricity in real time, the operating characteristics of each appliance and the level of satisfaction/comfort of the consumer. Thus, when HEMS is installed in residences, it is intended to minimize the cost related to the electricity consumption with the least possible interference to the satisfaction/comfort of the end consumers and to guarantee the stability and efficiency of the electric power system.

The HEMS developed in this thesis consists basically in 03 main components: Advanced Measurement Infrastructure (AMI), Smart Meters (SM) and Energy Management Controller (EMC). All the procedures performed, for example, turn on/off home appliance loads, are supported by a data network, such as ZigBee (IEEE 802.15.4) (RAMYA; SHANMUGARAJ; PRABAKARAN, 2011), which conveys information of the home appliance operations to the EMC, using it to determine the system status and rehearse the commands to be performed.

Advanced Measurement Infrastructure enables bi-directional communication between SMs and the utility, allowing real-time data sharing of electricity consumption and pricing. The SM is a communication interface installed between AMI and EMC to collect data related to the energy consumption of each home appliance using, for example, technology ZigBee, Z-wave or Bluetooth, and it receives real-time information about the electricity price from the utility. The EMC (HEMS operating core) is fully responsible for the usage management of the existing devices on the home network.

Under these circumstances, the EMC, using the DR optimization model presented in this thesis, can plan the use of each home appliance minimizing the cost related to energy consumption and the inconvenience level of consumers through the scheduling of the load usage pattern, based on the price of electricity and provide *a priori* in order to guarantee the stability and safety of the EPS.

1.5 Thesis Statement

This thesis proposes a HEMS that is able to plan the operation of the residential appliances considering the data obtained on energy consumption of each appliance, the real-time pricing of electricity and end consumer usage preferences. The HEMS controls and managements the home appliances more accessible in order to reduce the cost related to electricity consumption and the inconvenience level caused by the use of the appliances, and it results in a lower peak-to-average ratio (PAR), which contributes to improving the reliability of the EPS operation. Specifically, the thesis statement is:

Due to the costs and restrictions related to energy, HEMS is of great importance nowadays because it is becoming essential for modern societies, cities, and smart homes (ARAÚJO *et al.*, 2018; SILVA; KHAN; HAN, 2018). HEMS manage home energy consumption in order to increase the stability and efficiency of the EPS using the optimization algorithms.

Thus, different techniques are being studied to improve residential energy usage. The main technique to improve energy usage is by adjusting the planning of residential appliances to maximize consumption. Such adjustments allow a reduction in the final amount of energy required and, by operating the appliances in periods when the cost of electricity is lower, reduce the final costs even further; moreover, the use of appliances in off-peak hours with cheaper rates reduces the demand during peak-hours (HEMMATI; SABOORI, 2017; SHAKERI *et al.*, 2018).

End consumers have home appliances (FANG *et al.*, 2012; GAO *et al.*, 2012; VARDAKAS; ZORBA; VERIKOUKIS, 2015) that need to be programmed in an orderly manner to guarantee a balance between supply and demand of electric energy (FANG *et al.*, 2012; PIPATTANASOMPORN *et al.*, 2012; VARDAKAS; ZORBA; VERIKOUKIS, 2015). However, the programming of these home appliances within the same time interval requires specific knowledge and availability of time on the part of the consumer (RASTEGAR; FOTUHI-FIRUZABAD, 2015). Also, residential management scheduling must grant consumer preferences regarding the usage of these appliances and the price variation of electricity.

To support this thesis statement, the following research approach was adopted:

Considering the importance of load scheduling in the residential area, the different categories of residential appliances and consumer preferences were carefully investigated. Through these studies, the achievements in this area were identified, as well their limitations and open issues. An analysis of the solutions for the optimized scheduling of residential appliances was conducted to evaluate the efficiency of HEMS, that uses the DR optimization model in its operational core (EMC) in scenarios and it involves the cost minimization associated with the consumption of electric energy as well as minimizing the level of inconvenience (dissatisfaction / discomfort) of end consumers.

Thus, several experiments have been implemented in order to verify the performance of HEMS using a multi-objective DR optimization model mathematically formulated as nonlinear programming (NLP) problem to determine optimal programming of the appliances, considering real-time pricing (RTP) and the different categories of home appliances. This DR multi-objective optimization model aims to minimize the cost related to the electricity consumption and the inconvenience for the end consumers subjected to a set of restrictions, such as minimum and maximum load limits for each time interval; ramp limits; minimum consumption related to the time horizon; and operational constraints for the different home appliance categories.

1.6 List of publications

Given the aforementioned contributions, the more prominent publications on the scope of this doctoral thesis are listed below:

1. **Um Modelo de Otimização de Resposta à Demanda para Consumidores Residenciais Considerando as Categorias de Eletrodomésticos**
   Silva, I. R. S., Veras, J. M., Rabêlo, R. A. L. and Pinheiro, P. R.
   In XIII Simpósio Brasileiro de Automação Inteligente (SBAI 2010), Porto Alegre, RS, Brasil, 01 a 04 de outubro de 2017, pp. 1460–1467.
   ISSN: 2175 8905
2. **A Demand Response Optimization Model for Home Appliances Load Scheduling**
   Veras, J. M., Pinheiro, P. R., Silva, I. R. S. and Rabêlo, R. A. L.
   In International Conference on Systems, Man, and Cybernetics (SMC 2017), Banff Center, Banff, Canada, October 5-8, 2017, pp. 2915-2920.
   DOI: 10.1109/SMC.2017.8123070
3. **Um Modelo de Otimização Multi-Objetivo de Resposta à Demanda para Gerenciar as Cargas Residenciais**
   Veras, J. M., Silva, I. R. S., Rabêlo, R. A. L., Pinheiro, P. R. and Rodrigues, J. J. P. C.
   In XXII Congresso Brasileiro de Automática (CBA 2018), João Pessoa, PB, Brasil, 09 a 12 de setembro de 2018, pp. 1-8.
   DOI: 10.20906/CPS/CBA2018-0568
4. **Towards the Handling Demand Response Optimization Model for Home Appliances.**
   Veras, J. M., Silva, I. R. S., Pinheiro, P. R., Rabêlo, R. A. L.
   Sustainability, vol. 10, no. 3, pp. 616–633, 2017.
   DOI: 10.3390/su10030616
5. **A Multi-Objective Demand Response Optimization Model for Scheduling Loads in a Home Energy Management System.**
   Veras, J. M., Silva, I. R. S., Pinheiro, P. R., Rabêlo, R. A. L., Veloso, A. F. S., Borges, F. A. S. and Rodrigues, J. J. P. C.

Sensors, vol. 18, no. 10, pp. 3207–3231.
DOI: 10.3390/s18103207

1.7 Work Organization

This thesis has 05 Chapters, after this introduction; they are the following:

Chapter 2 presents the theoretical foundation, which details the concepts of a smart grid, demand response, mono-objective and multi-objective optimization problems, optimization techniques (Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Language for Interactive General Optimizer (LINGO) and Non-dominated Sorting Genetic Algorithm II (NSGA-II)) and gives the scientific productions developed in the literature, assuming DR tariff models (TOU, RTP, and CPP) to perform the classification of the papers studied in the course of this work.

On the other hand, in Chapter 3 explains the Home Energy Management System (HEMS) describing its main components, detailing the proposed DR optimization model to manage the load scheduling in residential environments. Thus, the various restrictions associated with energy consumption are explained here, such as the minimum and maximum limits of the load for each time interval; ramp limits; minimum consumption related to the time horizon; and operational restrictions of the home appliance categories.

Besides, in chapter 4 discusses the performance evaluation and analysis of the results obtained through computational simulations using LINGO, GA, PSO and NSGA-II metaheuristics in mono-objective and multi-objective contexts, respectively. Moreover, the statistical metrics that were used to evaluate HEMS operation before the load scheduling process through NSGA-II using the DR multi-objective optimization model are also presented. Furthermore, other test scenarios and a comparative analysis of the achieved results for different energy consumption profiles and different categories of residential appliances were discussed.

Finally, Chapter 5 gives the conclusions of the thesis, with emphasis on the main contributions, the results achieved and the perspectives for future works.

Chapter 2

THEORETICAL FOUNDATION

This Chapter describes the theoretical basis, which introduces relevant concepts about smart grids, demand response, mono-objective and multi-objective optimization problems, optimization techniques (Genetic Algorithm (GA), Particle Swarm Optimization (PSO), LINGO and the Non-Dominated Sorting Genetic Algorithm II (NSGA-II)). It also presents the scientific proposals related to the Home Electricity Consumption Management in the Smart Grids according to the type of tariff model: Time-Of-Use, Real-Time Pricing and Critical- Peak Pricing.

2.1 Smart Grid (SG)

During the twenty-first century, the electricity demand increased significantly, and this brought various practical problems, such as difficulties to attend peak power demands, with voltage fluctuations and outages. Nowadays, as contemporary society is highly dependent on electricity, there is a strong need for an energy system that is as reliable and secure as possible (PIPATTANASOMPORN *et al.*, 2012).

Thus, a new paradigm for the electric power system (EPS), called a smart grid (SG), has emerged. The SGs infrastructure is composed of energy, information, and communication architecture and provides to consumers the possibility of producing their electricity (through photovoltaic panels, for example) and send back to the grid the energy that was not consumed during the day, enabling a two-way energy network. Meanwhile, the traditional electric power system (EPS) operates unidirectionally, in other words, the electric power is transported by the transmission system and distribution from the generation plants to the consumers in a single direction (BHAROTHU; SRIDHAR; RAO, 2014).

Figure 1 represents a traditional electric power system, which mainly utilizes hydroelectric plants as electricity generators. They produce 19.710,4 TWh of the energy consumed in the world (EMPRESA DE PESQUISA ENERGÉTICA (EPE) / MINISTÉRIO DAS MINAS E ENERGIA (MME), 2015), that is transmitted/distributed unidirectionally to end consumers, considering that most homes, buildings, and industries still do not produce their electricity and that few utilities are prepared for a two-way smart grid system.

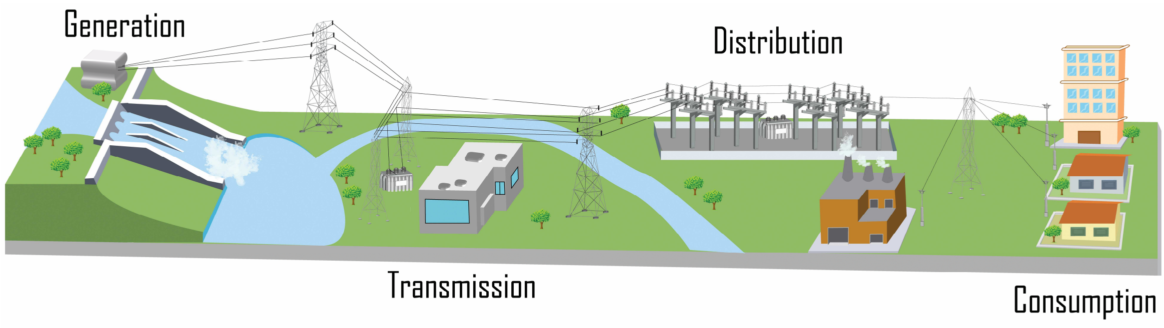

Figure 1 – Traditional Electric Power System.

The SG enables the improvement, reliability, and efficiency of generation, transmission, distribution and consumption of electric energy (FANG *et al.*, 2012). One of the benefits of an SG is the intensive use of information and communication technologies (ICT) that allows a greater automation of the electric power system. In addition, another benefit SGs is greater use of alternative sources of electricity, which have a lower environmental impact than the more traditional forms of energy generation, such as the sources derived from fossil fuels.

In power transmission and distribution systems, it is possible to use technologies that can, for example, monitor and control the magnitude of voltage in real time, in order to meet the electric energy demands of the end consumers (IEC, 2010). Regarding consumption, the use of bidirectional communication technologies between the concessionaire and the consumers can be applied to carry out various tasks remotely, such as measuring electricity consumption or interrupting the supply of electricity to consumers with outstanding debts (FAN *et al.*, 2013).

A Smart Grid seeks the integration of power systems and ICTs (IEEE STD 2030-2011, 2011) so that it can detect and analyze faults; notify consumers and network administrators; restore itself automatically and quickly; resist physical and cyber-attacks; meet the energy consumption profile of end consumers; provide quality energy and consistent with consumer needs; support the inclusion of a variety of resources, such as renewable energy production and demand response programs; and be accepted in competitive markets for electric power supply (FANG *et al.*, 2012; GAO *et al.*, 2012; SINHA *et al.*, 2011; VARDAKAS; ZORBA; VERIKOUKIS, 2015).

2.1.1 Smart Grid Architecture

A smart grid has a variety of mechanisms that are able to improve the operational stages of generation, transmission, distribution, and consumption. Among the mechanisms available, about the process of electric power generation, it can overcome the failures and the oscillations resulting from the energy production coming from renewable sources, by adjusting the use of the thermoelectric and hydroelectric plants (IEC, 2010).

In the transmission and distribution processes, SGs are used in the energy management systems; in decision support systems; in system integrity protection projects; in power electronics; in asset management and monitoring device systems; in automation and protection of distribution; in the management of distribution systems and Advanced metering infrastructure (AMI). Moreover, for the end-users, the SGs take part in smart consumption; local production; intelligent homes and building automation and overall control systems (IEC, 2010).

The communication system is a key component of the infrastructure of smart grids. This system integrates applications and computing technologies and makes the architecture of the grid capable of obtaining data from various appliances for further analysis, control and methods of charging in real-time (GÜNGÖR *et al.*, 2011). Therefore, the electric utilities must redefine their communication requirements in order to find the best infrastructure to handle this transfer of information.

Smart Grids have two forms of communication and networking for the flow of information: (a) the information collected from sensors, appliances or other equipment is sent to a smart meter, which calculates and provides the immediate need for electricity and then this information is sent to the global operating sector, allowing control of interconnected devices or equipment, and (b) information from a smart meter is sent to the SG infrastructure to control and adjust the generation, transmission and distribution of real-time energy (CHEN *et al.*, 2010).

The authors in (GAO *et al.*, 2012) claim that the Smart Grid incorporates information communication technologies into the grid. The SG participates throughout the current electrical grid system, from generation to transmission, and on to distribution (Figure 2). However, all these need to have an effective data communication networking system.

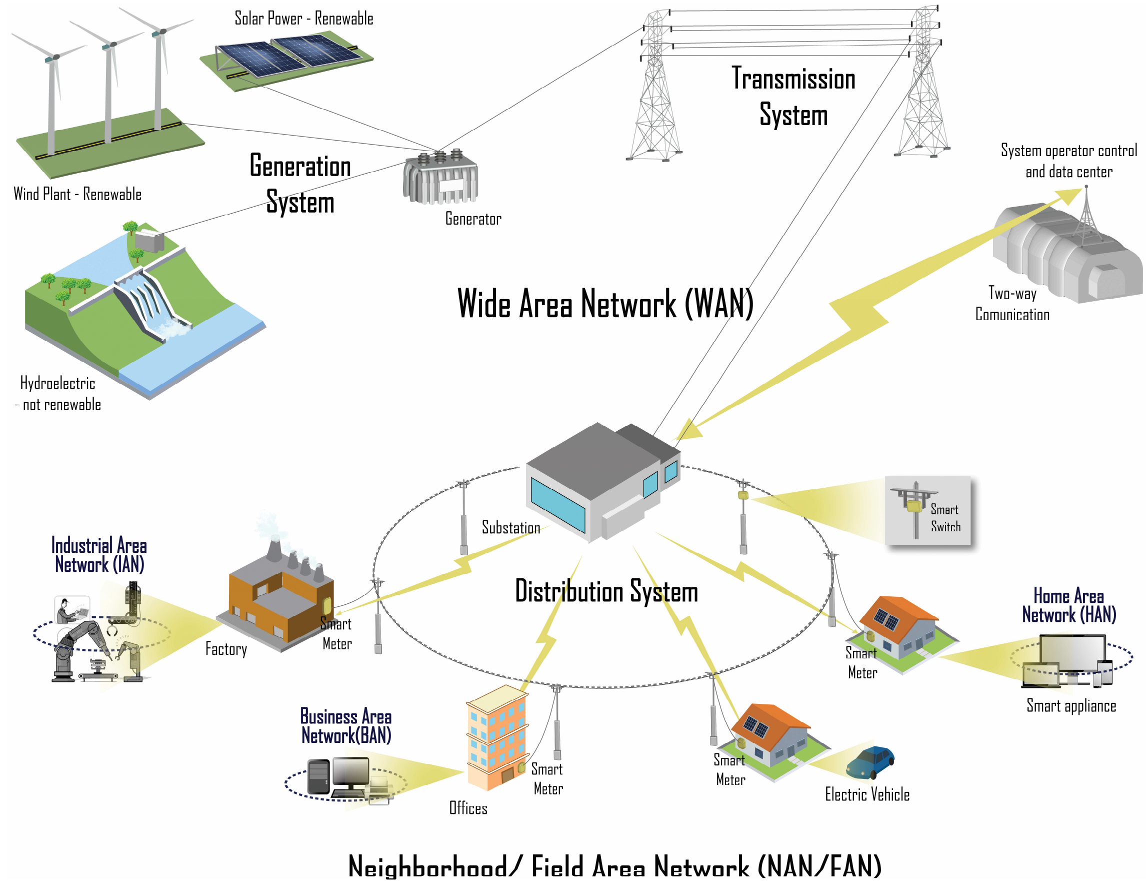

Figure 2 – Smart Grid Architecture.

A Smart Grid has Home Area Networks (HANs), Building Area Networks (BANs), Industrial Area Networks (IANs), Neighborhood Area Network (NAN), Field Area Network (FAN), and a Wide Area Network (WAN). HAN is a communication network for domestic appliances and devices; NAN and FAN are a network of multiple HANs that sends the metering data to data concentrators and control data to HANs; WAN is the largest network for communications to/from data centers. All the smart appliances in a HAN can be connected to smart meters. Smart appliances like smart dishwashers, dryers, ovens, etc.; have communications and remote control functions, and their smart meters are connected to a metering gateway.

In a NAN, the metering gateways of home areas can be connected to form a wireless mesh network. On the other hand, a WAN connects smart metering gateways with the utility and the distribution control system. However, there are many challenges to set up a practical Smart Grid Communication Infrastructure including interoperability and scalability with many different utility companies and user facilities as well as the need to incorporate new technology such as Smart Meter Infrastructure (GAO *et al.*, 2012).

2.2 Demand Response (DR)

The authors in (ROH; LEE, 2016) point out that many countries want to develop a smart grid to be able to utilize their energy resources efficiently using the electricity grid. Thus, an ordinary grid becomes smart by combining the electricity grid with a communication network, and real-time two-way communications are set up between grid and customer. However, there are still many challenges to overcome on setting up a smart grid, and demand response (DR) (or electricity load scheduling) plays a key role in order to run the smart grid efficiently and reliably (MEDINA; MULLER; ROYTELMAN, 2010).

DR is considered by the authors in (ALIPOUR; ZARE; ABAPOUR, 2017; MOON; LEE, 2016) to be a program that encourages the end consumers (residential, industrial and commercial) to change their energy consumption habits, based on price variations or incentive cash payments offered by utilities. These incentives produce reasonable prices as well as providing reliability to the system during peak periods. This makes DR interesting for the consumers and utility, especially when there is a high demand (PARVANIA; FOTUHI-FIRUZABAD, 2010; SIANO, 2014). Customers can schedule their energy consumption and the operations of their appliances with DR in order to reduce their electric bill and/or improve their satisfaction due to different electricity prices, and consequently their demand and preference profiles (ROH; LEE, 2016).

Demand response is classified into two programs, as shown in Figure 3, based on price and incentive (PARVANIA; FOTUHI-FIRUZABAD, 2010; PIPATTANASOMPORN *et al.*, 2012). The first is associated with changes in electricity consumption triggered by changes in the purchase price of electricity throughout the day. The second offer incentives (such as credits, discounts on the energy bill or cash) to consumers in order to reduce electricity consumption during the peak times (VARDAKAS; ZORBA; VERIKOUKIS, 2015). Both programs are described below.

2.2.1 Classification of DR Programs (DRPs)

The Incentive-Based Programs (IBP) are divided into Direct Load Control (DLC), Interruptible/Curtailable Services (ICS), Emergency Demand Response

Program (EDRP), Capacity Market (CM), Demand Bidding/Buyback (DBB) and Ancillary Services Market (ASM). In Price-Based Programs (PBP), the tariff models can be Time-of-Use (TOU), Real-Time Pricing (RTP) or Critical-Peak Pricing (CPP) (AGHAEI; ALIZADEH, 2013; FARIA; VALE, 2011; NAIR; RAJASEKHAR, 2014).

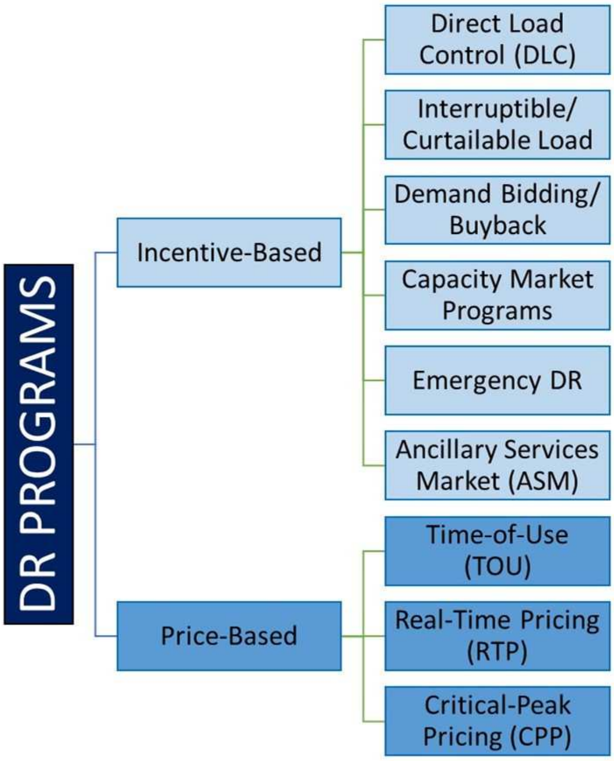

Figure 3 – Demand Response Programs.

2.2.1.1 Incentive-Based Programs (IBP)

This program offers incentives such as credits and discounts on energy bills or cash payments to consumers in order to reduce their energy consumption during peak periods. However, all the applications and responses of consumers to this program are voluntary; moreover, some of the existing programs penalize participants for their failure to comply with contractual clauses, such as the non-reduction of electricity consumption at a pre-determined time (VARDAKAS; ZORBA; VERIKOUKIS, 2015).

a) Direct Load Control (DLC):

Direct Load Control allows the program operator, manager responsible for the control of the energy system, to remotely access the shutdown or cycle of electrical equipment of consumers such as air conditioners or water heaters (FARIA; VALE, 2011; SIANO, 2014; ZHANG *et al.*, 2017). However, the authors in (CHEN; WANG; KISHORE, 2014) claim that the DLC programs have several limitations, such as:

I. They are only for emergencies since they do not analyze the operational flexibility of the equipment sufficiently to balance supply and demand;

II. The centralized control structure of these programs lack computing and communication requirements when a large number of clients are considered;

III. DLC programs lack effective control of customer privacy, due to the exposure of their energy consumption profiles every time equipment is remotely controlled.

b) Interruptible/Curtailable Service (ICS):

This program aims to reduce energy consumption by providing incentives in the form of credit or discounts on the energy bill. However, it is necessary for the consumer to be enrolled in the program so that they can take advantage of the benefits or suffer the penalties if they do not comply with the contractual clauses (FARIA; VALE, 2011; SHARIATZADEH; MANDAL; SRIVASTAVA, 2015; SIANO, 2014).

c) Emergency Demand Response Program (EDRP):

Emergency Demand Response Program is seen as a combination of the DLC and ICS programs but with the particularity of providing payments, such as discounts or credits on the energy bill, to consumers who achieve a satisfactory reduction in electrical loads during the periods when energy reserves are insufficient (FARIA; VALE, 2011; SIANO, 2014).

d) Capacity Market (CM):

Capacity Market allows consumers to pledge a reduction of electricity usage in a pre-determined manner, but they are prone to penalties if they do not reduce their consumption when prompted. Therefore, this program can be seen as a safe investment in the short and long terms, because the consumers reduce their energy consumption on request and, in return, they receive financial incentives (loans, discount rates on their energy bills or cash payments) (AALAMI; MOGHADDAM; YOUSEFI, 2010).

e) Demand Bidding/Buyback (DBB):

This program aims to encourage consumers, particularly industrial consumers, to reschedule their energy consumption and also to reduce consumption at peak times, in return, the utility offers financial rewards such as discounts on the energy bill. Also, consumers who have alternative sources of power generation are encouraged to sell the energy that was not used to the utility (SAEBI, J.; JAVIDI, 2012).

f) Ancillary Services Market (ASM):

The authors in (FARIA; VALE, 2011) claim that the ASM programs are similar to DBB, but when the ASM consumers reduce their electricity consumption they receive payments from the network operator, due to their support for the grid operations, that is as an auxiliary service (SIANO, 2014).

2.2.1.2 Price-Based Programs (PBP)

This program is linked to the changes in energy consumption in response to the existing variations in the price of electricity throughout the day. Here, the price-based program encourages consumers to change their energy consumption habits by following the changes in electricity prices. Consequently, consumers will decrease the use of electricity when prices are high and, as a result, there will be a reduced demand at peak times (DENG *et al.*, 2015; VARDAKAS; ZORBA; VERIKOUKIS, 2015).

a) Time-of-Use (TOU):

The TOU pricing is offered by utilities to customers. TOU offers different rates for different periods of the day (SHAO *et al.*, 2010; WANG *et al.*, 2013b); consequently, consumers modify their electricity use profile. This DR program is mainly aimed at residential users (LUJANO-ROJAS *et al.*, 2012). Usually, it reflects the average cost of generation and delivery of power over different periods (FARIA; VALE, 2011).

The authors in (GYAMFI; KRUMDIECK; URMEE, 2013) allege that the programs which investigate the impact of tariffs on electricity demand typically use the TOU model. Figure 4 presents a TOU pricing example in which the usual price of a kWh is US$ 0.50 but in the peak period between 11h00 and 14h00 this rate increases by approximately 60% to US$ 0.80 a kWh. Thus, TOU pricing confirms that a kWh of electricity at peak times costs much more than at other times.

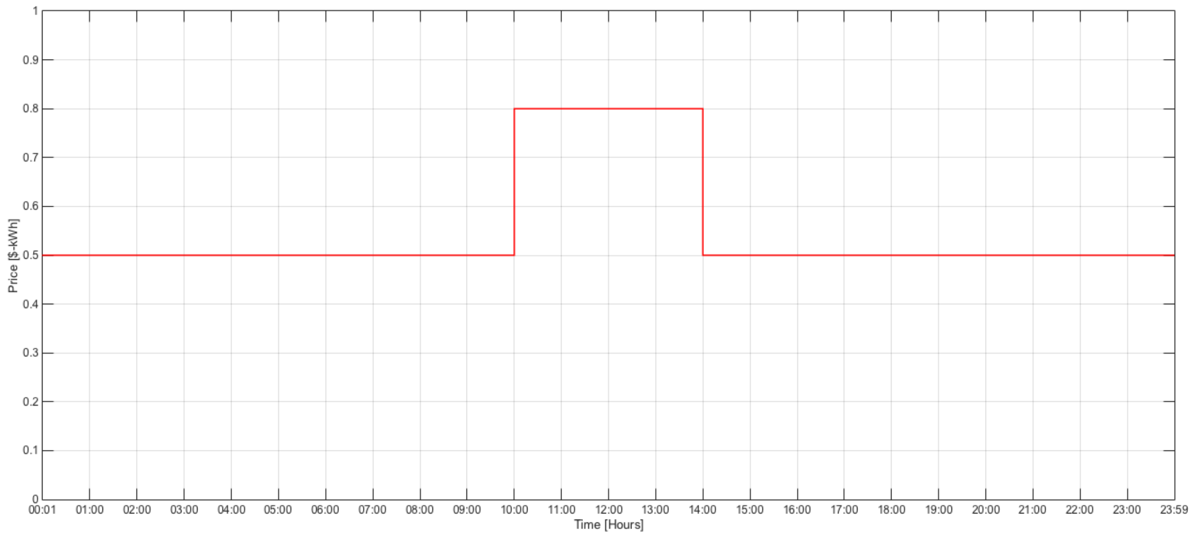

Figure 4 – TOU Price Structure.

TOU pricing programs allow the use of a price structure that considers periods with pre-established rates. However, the TOU can also be used in a dynamic pricing structure where there is a relationship between the real-time demand and the energy supply, harmonizing the balance of the use of energy and reducing the costs for the end consumers (XING YAN *et al.*, 2015).

b) Real-Time Pricing (RTP):

Greater participation by the consumers is extremely important in the RTP structure (VARDAKAS; ZORBA; VERIKOUKIS, 2015) because, in RTP, the price changes on an hourly basis and consumers are usually informed about the RTP price only hours or days in advance (WANG *et al.*, 2013b).

Figure 5 shows an RTP model in which the price of electricity varies hourly and the period with the highest tariff is between 19h00 and 20h00 and lowest price is between 00h00 and 1h00 a.m. However, the authors in (VARDAKAS; ZORBA; VERIKOUKIS, 2015) stated that the use of two-way communication technology is necessary to fully develop the RTP structure in SGs, as there must be a direct link in real-time between the utility and the consumer. Therefore, an Energy Management Controller (EMC) capable of supporting the continuous flow of data and consumer preferences is installed in the consumer environment, enabling significant improvements in the decision-making process about consumption and as a result, a reduction of costs.

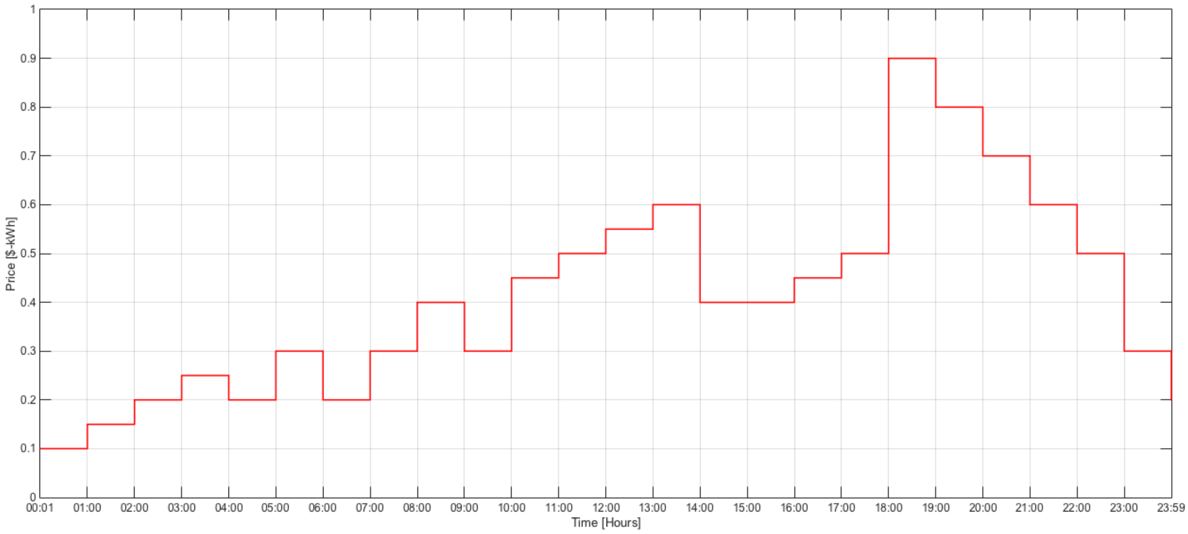

Figure 5 – RTP Price Structure.

Utilities also have a decision-making feature, which contemplates random events such as the total energy consumption and the consumer response compared to previous prices, allowing the new prices to be fixed for the next consumption period. The RTP program has already been successfully applied to various consumers in the industrial and commercial fields but has gained little success in residential areas, because most residential consumers consider the need to make periodic decisions about their electricity consumption a disadvantage (VARDAKAS; ZORBA; VERIKOUKIS, 2015).

Due to the technical limitations existing about demand, the implementation of real-time charging is still considered a challenging problem. However, it is very advantageous for owners of electric vehicles, which are usually recharged at night, when the tariffs are usually lower (XING YAN *et al.*, 2015).

c) Critical-Peak Pricing (CPP):

CPP is a hybrid-pricing model made up of TOU and RTP tariffs. According to the authors of (DENG *et al.*, 2015; WANG *et al.*, 2013b), the base structure for the CPP rate is TOU. However, the CPP uses the RTP charging structure when the electric system is facing risks, such as an energy demand greater than the supply, which affects reliability. Thus, the peak hour tariff is increased in order to reduce the energy demand. So, the increase in the tariff is linked to an increase in demand or low productivity of the system.

The example of the CPP in Figure 6 shows that the tariff structure is similar to TOU and the price, in kWh, is US$ 0.50 for most of the day. However, there were 2 critical events on that day: the first was between 11h00 and 12h00, when the tariff was adjusted to US$ 0.90 equivalent to an approximate increase of 80% compared to the value of the usual rate of US$ 0.50; and, the second critical event was between 18h00 and 19h00 when the tariff increased to US$ 0.80, representing an increase of approximately 60% over the normal off-peak hour tariff of US$ 0.50.

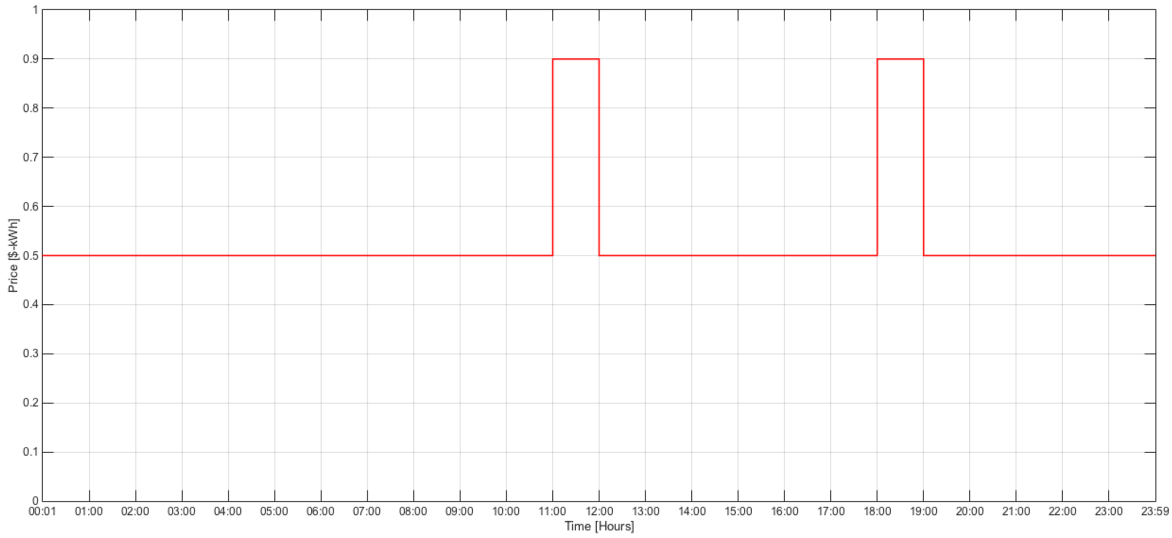

Figure 6 – CPP Price Structure.

Considering the above, CPP is used only for a limited number of hours or days per year, to ensure the reliability of the system or to balance demand and supply (VARDAKAS; ZORBA; VERIKOUKIS, 2015).

2.2.2 Demand Response Program Participants

The demand response program aims to balance the relationship between supply and demand of electricity. According to (SIANO, 2014), when consumers participate in the DR, there are various possibilities for them to change their energy consumption, such as: reduce their energy consumption through load reduction strategies and moving the energy consumption to non-peak periods. However, it is fundamentally important to know the consumer behaviour profile in order to establish answers to the changes in electricity prices over the periods and the threats related to system reliability (VARDAKAS; ZORBA; VERIKOUKIS, 2015).

The contribution and collaboration between the participants that make up the DR are of fundamental importance.

Figure 7 illustrates the four major players in the DR program: 1. The consumers who may be residential, commercial or industrial; 2. The DR Aggregator running the DR program that is inter-connected to the consumers; 3. The Distribution System Operator (DSO) that controls the distribution network; and 4. The Independent System Operator (ISO) or Regional Transmission Operator (RTO) that starts the operation of the DR program (VARDAKAS; ZORBA; VERIKOUKIS, 2015).

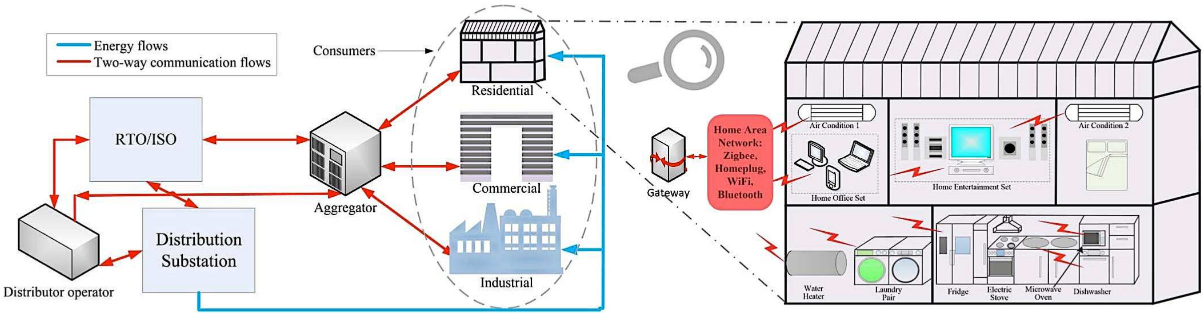

Figure 7 – Participants of DR Programs.
(VARDAKAS; ZORBA; VERIKOUKIS, 2015)

Figure **7** shows the participants of the DR program. The RTO/ISO starts the operation of the DR program, and then determines the required demand and consumption time period; information which is sent to the DR Aggregator. The DR Aggregator, in turn, chooses the consumer participants depending on their availability and their ability to the DR program proposal. Then, the DR Aggregator calculates the total demand and sends the data to the RTO/ISO. However, in order to avoid any possible problems occurring in the distribution system, the DR Aggregator notifies the total DR to the Distribution System Operator (DSO) that informs the substations with the most energy available about the total energy demand (VARDAKAS; ZORBA; VERIKOUKIS, 2015).

2.2.3 Benefits of Demand Response

According to O′Connell *et al.*, (2014), the inclusion of ICT and the increased ability to forecast power needs and control in electric power systems, makes DR a viable and appropriate option to improve load flexibility. Demand response allows a more efficient use of system resources, and as a result, DR may bring different benefits that are not just limited to reducing the operating costs of the system but have the possibility of including renewable energy sources, an increase in economic efficiency through the implementation of real-time prices, and finally reductions in generation capacity requirements, as well as transmission and distribution network congestion management. Bradley, Leach and Torriti (2013) also presented various important potential benefits of DR:

1. Relative and absolute reductions in electricity demand that are related to increased cost savings for consumers by economizing electricity and decreasing CO_2 emissions;

2. Short run marginal cost savings by using DR to shift peak demand and to modify consumer usage patterns of electricity and consequently reduce the cost of electricity per kWh;

3. Ability to relocate new investments by using DR to shift peak demand, so that peak time loads are lower than they would be without the use of demand response;

4. DR can be used to provide reserves for emergencies/unforeseen events, especially in the short term, to allow the energy system to reduce electrical demand in an emergency;

5. DR is able to achieve a balance between supply and demand in a distributed electrical power system using renewable and non-renewable sources;

6. To reduce transmission network investments by reducing congestion of the network and avoiding transmission network re-enforcement;

7. Moreover, finally, DR can be applied to improve distribution network investment efficiency and reduce losses.

According to Siano (2014)**,** DR can offer many benefits related to the operation and expansion of the system and marketing efficiency depending on the purpose, design, and implementation, as well as other factors such as the technology used and the system structure. Thus, the benefits of DR can be classified, considering the participants involved in general or only some members or all groups of electricity consumers, as follows:

1. Savings in electricity bills: the participants receive payments for modifying their energy consumption;

2. Reliability: consumers who are active participation in the electrical system, such as those that generate electricity through renewable sources and

concede any non-consumed energy to the power utility, help avoid deficits in the electrical system;

3. Market performance: DR prevents a monopoly of the market by the electric utilities as various sectors (industrial, commercial, residential) become active in the generation and sale of electricity;

4. Improvement of choice: consumers have more choices regarding the management of the tariffs;

5. System Security: the electrical system operators are given more flexibility, and for example, are able to interrupt or switch loads remotely in order to overcome any contingencies.

Thus, DR, from the point of view of smart grids is an effective means of rescheduling consumer energy consumption and enabling the whole system to become more reliable and transparent regarding expenses laid out in the electricity bill; moreover, DR allows the utilities to offer an electricity market suitable for end-users. Consequently, there are financial benefits for the power utility and the consumers, and last but not least, DR helps reduce impacts on the environment with the inclusion of alternative sources of electricity generation as well as making more efficient use of the grid capacity (DENG *et al.*, 2015).

2.2.4 Barriers to Demand Response

The elements that can prevent or restrict DR operations are called barriers. These barriers can be processes, people, policies, organizations or any other aspect of the electric power industry (HODGSON; THOMSON; CLIFFORD, 2011) However, the origin of these barriers is linked to socio-economic, technical-economic situations or policies, which can be identified as: Technological, Regulatory and Economic (HODGSON; THOMSON; CLIFFORD, 2011; THE BRATTLE GROUP; FREEMAN SULLIVAN & CO; GLOBAL ENERGY PARTNERS, 2009).

a) Technological Barrier:

Technological barriers involve the following: Lack of Advanced Metering Infrastructure (AMI); Lack of Cost-Effective Enabling Technologies; Concerns about Technological Obsolescence and Cost Recovery; and Lack of Interoperability and Open Standards (HODGSON; THOMSON; CLIFFORD, 2011; THE BRATTLE

GROUP; FREEMAN SULLIVAN & CO; GLOBAL ENERGY PARTNERS, 2009). However, Lack of Advanced Metering Infrastructure causes a serious problem on setting up a DR program based on price, as there will be no capacity to measure the data and therefore the DR program will not be able to offer consumers dynamic pricing.

A Lack of Cost-Effective Enabling Technologies affects the participation of consumers in DR programs because technologies, such as smart thermostats that respond to high prices through an automatic adjustment in their settings aimed at energy savings, are not yet profitable for the electric utility. The concerns about the Technological Obsolescence and Cost Recovery involve doubts about the ability to recover the cost of these investments before these technologies need to be replaced. Finally, the Lack of Interoperability and Open Standards can harm the process of communication between devices, such as thermostats and smart meters, among others that are part of the demand response program (THE BRATTLE GROUP; FREEMAN SULLIVAN & CO; GLOBAL ENERGY PARTNERS, 2009).

b) Regulatory Barrier:

This barrier occurs when there is no legislation concerning the rights and obligations of the participants in the DR program. Therefore, the regulatory barrier is considered a serious problem for DR (HODGSON; THOMSON; CLIFFORD, 2011). The authors in (THE BRATTLE GROUP; FREEMAN SULLIVAN & CO; GLOBAL ENERGY PARTNERS, 2009) claim that the lack of a standard regulating the price of electricity affects the dynamic pricing being developed by the power utility for the consumers, because most of the tariffs currently offered do not reflect the dynamics of time (for example - every hour of the day) in the cost of supply. Thus, consumers are not provided with adequate prices and as a result, fail to carry out efficient energy consumption, causing them to consume more energy during peak periods.

c) Economic Barrier:

According to the authors in (THE BRATTLE GROUP; FREEMAN SULLIVAN & CO; GLOBAL ENERGY PARTNERS, 2009), the economic barrier is associated with two central obstacles. First: Inaccurate Price Signals, tariffed prices for the supply of electric energy do not accurately reflect the real value, and therefore may cause a reduction in demand when the cost of electricity is low or an increase in power consumption when the tariff is high, hindering the economic efficiency of the energy market. The second obstacle is the Lack of Sufficient Financial Incentives to Induce Participation that can lead to low participation of consumers in DR programs. However, existing higher financial incentives have increased the presence of consumers in DR programs.

Nair and Rajasekhar (2014) claim that one of the main obstacles to the inclusion of consumers in DR programs is the lack of a manual explaining the operational processes. Therefore, along with that latter reason, the lack of time, lack of knowledge and lack of interest by the consumer to actively participate in DR programs connected to the electric power system means that the DR programs are not growing as expected. Based on such data, various scientific works are being developed to seek a satisfactory outcome for DR about managing loads effectively, through the implementation of multiple "smart" devices capable of performing the automatic intervention in the management of electricity process for the consumer.

2.3 Optimization

According to Rey Nariño (2014), optimization problems aim to minimize or maximize a certain objective function, subjected or not to constraints of equality and inequality, thus achieving better use of available resources. Therefore, globally, Rey Nariño (2014) defines optimization as a research process for the best use of resources within a category of possible solutions from the project variables.

2.3.1 Mono-Objective Optimization

The mono-objective optimization aims to obtain values that involve minimizing or maximizing a single objective and scalar function (BARBOSA, 2012). Thus, when SG involves DR, one of the main purposes is to find solutions that allow the end consumer to minimize the cost associated with the electricity consumption and the level of dissatisfaction/discomfort in relation to the optimized programming of the use of the home appliances. On the other hand, one of the objectives of the electric utility is to maximize the profit, efficiency, and safety of the electric power system.

2.3.1.1 Mono-Objective Problem Formulation

The mathematical formulation of a mono-objective optimization problem is usually designed as (BAZARAA; SHERALI; SHETTY, 2006; MOUSSOUNI-MESSAD, 2009):

$$optimize\ f(x) \tag{1}$$

subject to

$$g_i(x) \leq 0, i = 1, \dots, l \tag{2}$$

$$h_i(x) = 0, i = 1, \dots, m \tag{3}$$

$$x \in X \tag{4}$$

In this formulation f, $g_i, \dots, g_l$, $h_i, \dots, h_m$ are functions defined on $\Re^n$, X is a subset of $\Re^n$, and x is the vector of the problem variables $x_1, x_2, \dots, x_n$, $f(x)$ is the objective function to be minimized (or maximized), $g_i(x) \leq 0, i = 1, \dots, l$ and $h_i(x) = 0, i = 1, \dots, m$ are the set of inequality and equality constraints of the problem respectively.

2.3.2 Multi-Objective Optimization

Many real-world problems come with a set of goals to be optimized that are often conflicting with each other, in other words, it is impossible to improve a goal without harming another. These problems are known as multi-objective or multi-criterion and are distinguished from classical mono-objective optimization problems in the way of solving them. Because they are conflicting objectives, each objective in a multi-objective optimization each objective corresponds to an optimal solution and the problems are presented as a set of optimal solutions (AMORIM, 2006).

According to Pavelski (2015), a Multi-Objective Optimization Problem (MOP) is mathematically formulated such as a) vector of decision variables that satisfy a set of constraints and; b) vector of objective functions to be optimized. The objective functions are usually in conflict with each other, so optimizing means finding solutions with acceptable values according to what is established for each objective. A more generic way to solve a MOP is to find a set of good solutions, supporting the tradeoff between the objectives. Then, it is up to the decision maker to provide a set of the best solutions using higher-level information and the power of choice, such as experience in a given situation. Hereupon, the search for efficient non-dominated solutions is independent of the problem.

2.3.2.1 Multi-Objective Problem Formulation

A multi-objective optimization problem (MOP) can be described as follows (AZUMA, 2011; TRIVEDI *et al.*, 2017):

$$optimize\ f(x) = (f_1(x), f_2(x), \dots, f_i(x))^T$$

subject to (5)

$$g_i(x) \le 0, i = 1, \dots, L \quad (6)$$

$$h_j(x) = 0, j = 1, \dots, M \quad (7)$$

$$x \in X \begin{cases} x_i^{(inf)} \le x_i \le x_i^{(sup)} \\ x \in \Omega \end{cases} \quad (8)$$

where Ω is the search space and x is the decision variable vector, representing the problem solution $f\colon \Omega \rightarrow \Re^i$, where i is the number of objective functions, and $\Re^i$ is the objective space and L and M are the number of inequality and equality constraints, respectively. Inequalities (g_i) and equalities (h_j) are known as constraint functions and the values $x_i^{(\mathrm{inf})}$ and $x_i^{(\mathrm{sup})}$ indicate the inferior and superior limits of the variable x_i. Therefore, these limits define the space of the variables and the set of all the possible solutions form the feasible region or search space (Ω). The vector of the objective function $f(x) = (f_1(x), f_2(x), \dots, f_i(x))^T$ belongs to the objective space. Thus, for each solution of x in the decision space, there is a point $f(x)$ in the space of the objectives (AZUMA, 2011; TRIVEDI *et al.*, 2017).

Aquino (2015) affirms that, in a multi-objective optimization, the concept of optimality is based on the definition of Pareto dominance to compare two feasible solutions to the problem introduced by Edgeworth in 1881 and, then, generalized by Vilfredo Pareto in 1896. Considering a minimization of all the objectives and given two solutions x and y, it is said that x dominates y (represented as $x \preccurlyeq y$) if the following conditions are satisfacted (AQUINO, 2015; AZUMA, 2011; TRIVEDI *et al.*, 2017):

- The solution x is better than or equal to y in all the objective functions, in other words $f_i(x) \le f_i(y)\ \forall_i \in \{1, \dots, i\}$, where m is the number of objective functions;
- The solution x is strictly better than y in at least one objective function, that is, $f_i(x) < f_i(y)$ for at least one value of i.

A solution that is not dominated by any solution of the space Ω is called Pareto-optimal, and its set is called the Pareto-Optimal Set. The respective points in the objective space determine a border called the Pareto-Optimal Frontier (AQUINO, 2015).

(AZUMA, 2011) displays in Figure 8 an example that illustrates the concept of dominance between the points of an objective minimization problem. In this picture, $B \preccurlyeq A$. Notice that A and B are solutions associated to different values of x although these points are being plotted in the space of the objectives and not in the space of the variables.

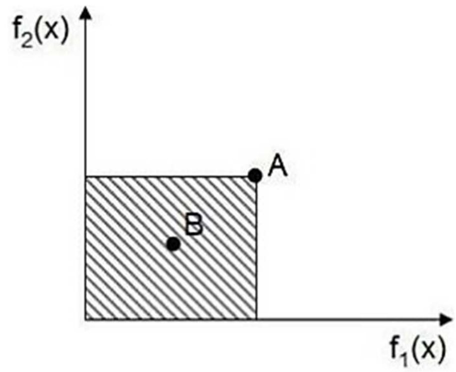

Figure 8 – Concept of dominance between points B and A.
(AZUMA, 2011).

2.4 Optimization Techniques

The operation of different categories of home appliances needs to be managed so that the cost related to electricity consumption can be minimized considering a scenario with variable electric energy prices as a function of the time interval. Thus, there is a need for a load scheduling method that requires little attention from consumers regarding configuration and maintenance yet allows the comparison of costs and benefits of different schedules for home appliances.

The optimization model used by HEMS through the EMC was formalized as a nonlinear programming problem subjected to a set of constraints associated with energy consumption and operational aspects related to home appliance categories. Therefore, the planning of loads must be made automatic with the use of optimization techniques such as the exact methods in order to find the best feasible solution considering the objective of the problem and the set of constraints.

Under these circumstances, Informs (1998) presents several computational tools to solve nonlinear problems, such as, Successive Linear Programming (SLP) and Generalized Reduced Gradient (GRG and GRG2), which have been used extensively for many years to solve nonlinear optimization problems in which the objective and constraint functions can have nonlinearities of any form but should be differentiable.

The Advanced Multidimensional Modeling System (AIMMS) features a mixture of declarative and imperative programming styles which allow mathematical optimization problems such as nonlinear programming to be solved. The Large-Scale Generalized Reduced Gradient (LSGRG) for a Mathematical Programming Language (AMPL) and AMPL Plus provides the ability to solve nonlinear models with integer variables. MINOS for AMPL using a variety of adaptive algorithms, MANOS can robustly solve problems with thousands of nonlinear constraints.

Lastly, LINGO is optimization software for mathematical modelling that allows solving various models such as linear, quadratic and general nonlinear integer models. LINGO separates the model in parts and, it solves the problem in each part in a different way because it has several techniques with advanced solutions such as cut generation, tree reordering to reduce tree growth dynamically, and advanced heuristic and presolve strategies. LINGO utilizes GRG and SLP for nonlinear (NL) models and Branch & Bound for NL and Linear Programming (LP) models with integer restrictions.

Hereupon, this thesis shows a DR optimization model used by HEMS through EMC in real time for residential consumers in order to minimize the cost related to the electricity consumption, with the least possible interference in the convenience level of the end consumers. Thus, the proposal was computationally solved by LINGO to determine a new usage scheduling of the home appliances for the whole time horizon.

2.4.1 LINGO

In 1988, LINGO became the first product of LINDO Systems to include a full featured modelling language. Users were able to apply the modelling language to express models using summations and subscripted variables concisely. In 1993, LINGO added a large-scale nonlinear solver. It was unique in that the user did not have to specify which solver to use. LINGO would analyze the model and would engage the appropriate linear or nonlinear solver. Also unique to the LINGO nonlinear solver was the support of general and binary integer restrictions. In 1994, LINGO became the first modelling language software to be included in a popular management science text. In 1995, the first Windows release of LINGO was shipped. Today, LINDO Systems continues to develop faster, more powerful versions (KRISHNARAJ, C.; JAYAKUMAR, A. ANAND; SHRI, 2015).

LINGO is a simple tool that uses the power of linear and nonlinear optimization to formulate large problems concisely, solve them, and analyze the solution. Optimization helps to find the answer that yields the best result; attains the highest profit, output, or happiness; or the one that achieves the lowest cost, waste, or discomfort. Often these problems involve making the most efficient use of your resources-including money, time, machinery, staff, inventory, and more. Optimization problems are often classified as linear or nonlinear, depending on whether the relationships in the problem are linear concerning the variables (LINDO SYSTEMS INC., 2016).

LINGO includes a set of built-in solvers to tackle a wide variety of problems. Unlike many modelling packages, all LINGO solvers are directly linked to the modelling environment. This seamless integration allows LINGO to pass the problem to the appropriate solver directly in memory rather than through more sluggish intermediate files. This direct link also minimizes compatibility problems between the modelling language component and the solver components (JAYAKUMAR; KRISHNARAJ, 2015).

Local search solvers are generally designed to search only until they have identified a local optimum. If the model is non-convex, other local optima may exist that yield significantly better solutions. Rather than stopping after the first local optimum is found, the Global solver will search until the global optimum is confirmed. The Global solver converts the original non-convex, nonlinear problem into several convex, linear subproblems. Then, it uses the branch-and-bound technique to exhaustively search over these subproblems for the global solution. The Nonlinear and Global license options are required to utilize the global optimization capabilities (KRISHNARAJ, C.; JAYAKUMAR, A. ANAND; SHRI, 2015).

2.4.2 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a population-based stochastic optimization method that was first described by James Kennedy and Russell C. Eberhart in 1995 (BAI, 2010). Various authors (CHHIKARA; SHARMA; SINGH, 2016; GAING, 2003; LEE; PARK, 2006; REZAEE JORDEHI *et al.*, 2015) claim that PSO has a relatively simple concept and coding system when compared with other heuristic optimization techniques and is therefore a popular method to solve optimization problems. Moreover, it is less sensitive than other conventional mathematical approaches and has a low computational cost. PSO techniques are able to produce high quality solutions in a shorter time frame and with greater stability than other stochastic methods, also the PSO methods require fewer parameters such as only the weight factor and two acceleration coefficients, which have less impact on the solutions compared with other heuristic algorithms.

According to Pedrasa, Spooner and Macgill (2010), PSO is able to find the solution to an optimization problem through simulation mechanisms of social behavior of animals (such as a flock of birds and shoals of fish), by analyzing a set of particles that navigate the space of solutions, in which its trajectory combines its experiences (solutions with better performance) and the best location they have visited.

Each particle has a position vector that represents the current position of the particle in the search space, and a velocity vector that is responsible for directing the particles in position changes in the search space. The idea of the algorithm is that the particles “fly over” the search space by updating the position of the particle. The velocity is updated based on the experience of each particle, having a memory of its best position and the collective experience, indicating the best position among all the particles (or of a neighbourhood of the particle) (ESMIN; COELHO; MATWIN, 2015). In PSO, the changes (velocity and position of each change) of the particles are described by the following equations (ESMIN; COELHO; MATWIN, 2015; PEDRASA; SPOONER; MACGILL, 2010):

$$v_{i,k}^{t+1} = v_{i,k}^{t} + c_1 r_1 (pbest_{i,k}^{t} - p_{i,k}^{t}) + c_2 r_2 (pgbest_{k}^{t} - p_{i,k}^{t}) \quad (9)$$

$$p_{i,k}^{t+1} = p_{i,k}^{t} + v_{i,k}^{t+1} \quad (10)$$

where $v_{i,k}^{t}$ and $p_{i,k}^{t}$ are the velocity and position of the i^{th} particles, respectively; c_1 and c_2 are two parameters representing particle confidence in itself (cognition) and in the swarm (social behavior), respectively; r_1 and r_2 are uniform random numbers distributed in the range (0,1); $pbest_i$ and $pgbest$ indicate the best positions experienced so far by the i^{th} particle and the whole swarm, respectively.

The particle positions and velocities are initialized randomly. Afterwards, they move around the solution space guided by Equations (9) and (10). The fitness of all particles is evaluated, and the global and personal best positions are updated if needed. The global best at the end of the simulation is taken as the solution to the problem (PEDRASA; SPOONER; MACGILL, 2010).

2.4.3 Genetic Algorithm (GA)

The genetic algorithm (GA) is part of the branch of evolutionary algorithms that was idealized by John Holland in 1975 (HOLLAND, 1975) and later popularized by David Goldberg. GA is defined as a search technique based on the representation of the biological process of natural selection proposed by Charles Darwin. Thus, the fittest individuals survive for the next generation, and GA represents the development of artificial systems that retain the important mechanisms of natural systems (LINDEN, 2012; REY NARIÑO, 2014).

Kumar (2013) and Linden (2012) show that Genetic Algorithms present several advantages in comparison to other methods (exacts and heuristics) in order to solve optimization problems, which are: (1) is much easier to implement as compared to other techniques as it requires no knowledge or gradient information about the response surface, (2) is the ease with which it can handle arbitrary kinds of constraints and objectives, (3) GAs do not only use local information, so they do not necessarily get stuck at local maxima, (4) GAs are able to handle discrete and continuous functions, (5) Optimization problems in which the constraints and objective functions are non-linear and/or discontinuous are not amenable to solution by traditional methods such as linear programming. GA can solve such problems and (6) GA use simple operations, but are able to solve problems, which are found to be computationally prohibitive by traditional algorithmic and numerical techniques.

According to Lucena (2013), the evolutionary process of the genetic algorithm is made up of several steps, illustrated in Figure 9:

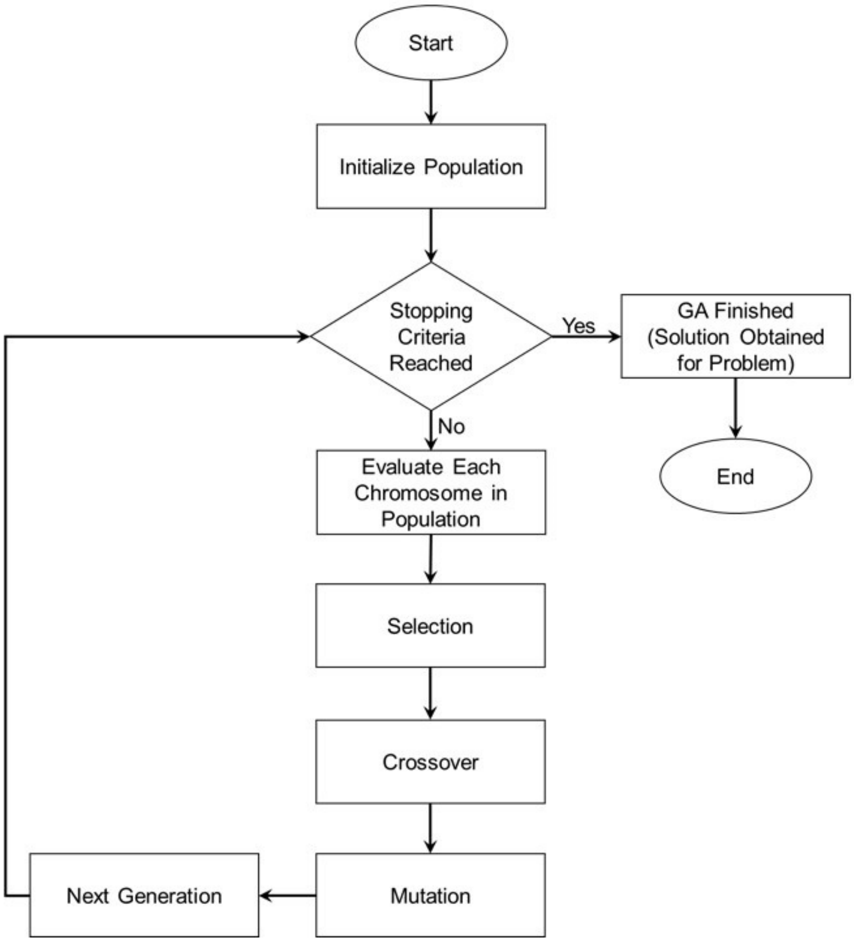

Figure 9 – GA Flow Chart.

Initializing the Population:

The first step of a typical GA is the generation of an initial chromosome population, which is formed by a random chromosome set representing feasible solutions of the problem to be solved (LACERDA; CARVALHO, 1999).

Evaluation:

During the evolutionary process, this population is evaluated, and each chromosome receives a grade (known as fitness obtained by the Equation (11), reflecting the quality of the solution it represents. Commonly, the fittest chromosomes are selected, and the least able are discarded. (LACERDA; CARVALHO, 1999).

$$Fitness = \frac{1}{\sum_{i=1}^{N} e_i \sum_{t=1}^{T} (pr_t * DSA_{t,i})^2 + 0.1} \tag{11}$$

Selection:

This GA step aims to select individuals for reproduction. Thus, individuals are selected considerations the aptitude of these individuals, in other words, the fittest individuals for a solution are most likely to be chosen for reproduction.

According to Gangwar, Din and Jha (2017) and Lucena (2013), the main selection methods are:

- **Rank:** individuals are organized into a ranking in accordance with their suitability. The probability of choice is assigned considering the position they occupy in the ranking;
- **Roulette Wheel:** it calculates the sum of the population rankings (total); it draws a value i such that $i \in [0; total]$; it selects the individual x which is located in the sum range of the corresponding to the value i ;
- **Tournament:** it randomly draws two or more k individuals who compete with each other and selects the fittest. The higher the value of k, the larger the GA selection pressure will be.
- **Steady State:** it is not only a method to select parents for the next generation, but it keeps the chromosomes with the highest fitness values for the next reproduction, replacing the bad chromosomes, those with lower fitness values, for new ones which have higher fitness values.

Lacerda and Carvalho (1999) stated that GA selects the best chromosomes from the initial population (with the highest fitness) to generate new chromosomes (which are variants of the parents) through the crossover and mutation operators. An intermediate population (also called mating pool) is used to allocate the selected parent chromosomes. Generally, parents are selected with proportional probability to their suitability.

Crossover:

In this stage, the crossover between individuals takes place in order to generate new individuals, children. The parents chosen by the selection method are divided into a randomly selected point called the cut-off point, producing two parts: one to the left of the cut-off point and one to the right. Thus, the parts are exchanged, generating two new chromosomes (LINDEN, 2012).

Kora and Yadlapalli (2017) and Lucena (2013) explains that the most used crossover operators are the 1-point, k-point, uniform and average, as detailed below:

1) 1-Point Crossover (1PX): this operator uses the single point fragmentation of the parents and then combines the parents at the crossover point to create the offspring or child. Two children/offspring are created by matching the parents at crossover point, in other words, in this type of crossover, a cut-off point is chosen in the genomes of the parents and part of each is given to the children, as shown below:

Parent 1:	1 0 1 0 | 1 0 0 1 0
Parent 2:	1 0 1 1 | 1 0 1 1 0
Offspring 1:	1 0 1 0 | 1 0 1 1 0
Offspring 2:	1 0 1 1 | 1 0 0 1 0

2) K-Point Crossover (KPX): similar to 1-point crossover, with the difference that there are k cut-off points, k is a fixed number. To achieve a good combination of parents i, t selects more than one crossover point to create the offspring or child. K-Point Crossover selects the two parents and then randomly selects k crossover points. Two children/offspring are created by the parents matching at the crossover point, for example:

Parent 1:	1 0 | 1 0 | 1 0 0 | 1 0
Parent 2:	1 1 | 0 0 | 1 0 1 | 1 0
Offspring 1:	1 0 | 0 0 | 1 0 0 | 1 0
Offspring 2:	1 1 | 1 0 | 1 0 1 | 1 0

3) Average Crossover (AX): this is a value-based crossover technique. It uses two parents to perform a crossover in order to create only one offspring and each gene in a child is taken by averaging the genes from both parents. It selects two parents as x and y and generates the child z as follows:

Parent 1:	5 3 3 2 3 8 7 6 5
Parent 2:	5 4 7 6 5 2 6 1 3
Offspring 1:	5 3 5 4 4 5 6 3 4

4) Crossover uniform (UX): in this crossover, there is uniformity in the bits matching of both parents. Commonly, a mask of 0 and one built in each crossover is used. In Uniform Crossover, one indicates that the gene will come from the first parent and 0 will come from another. To build the second child, the pattern is reversed, such as:

Parent 1: 1 11 0 1 0 0 1 0
Parent 2: 1 0 00 1 0 1 1 0
Offspring 1: 1 1 0 0 1 0 1 1 0
Offspring 2: 1 0 1 0 1 0 0 1 0

Mutation:

The mutation operator allows the characteristics of selected individuals to be changed to guarantee variety in the population. Thus, it is necessary for the mutation operator to associate an extremely low probability to it (of the order of 0.5%). Otherwise, GA will hardly converge to a good solution.

Lucena (2013) and Soni and Kumar (2014) present some kinds of mutations:

1) BitFlip: in this mutation, the gene to be mutated has its value altered by another, randomly drawn within the valid values. In this case (binary representation), this operator changes the value of the gene from 0 (zero) to 1 (one) and vice versa, for each 0 (zero) bit or 1 (one) a random percentage (0 to 100) is generated and, if that percentage is less than the mutation probability, the bit is inverted.

2) Scramble: it works as a permutation encoded chromosome, where n pairs of genes are drawn and the values of each pair are exchanged between them, in other words, a subset of genes randomly picked, and the alleles are rearranged in those positions.

3) Uniform: the mutation operator can only use integer and float genes in other to replace the values of the chosen one to use a uniform random value selected from the user specified upper and lower bounds for that gene.

4) Creep: in this mutation, a random gene is selected, and a random value is added to or subtracted from its gene to be mutated. Its value is changed between the lower and upper bounds, and real representation is used in this case.

Actualization:

At this stage, the newly created individuals are inserted into the population for the next generation.

Finishing / Stopping Criteria:

The GA ends its operation when the stopping criteria have been reached, and the GA closes on a positive case or returns to the evaluation step.

2.4.4 Non-Dominated Sorted Genetic Algorithm (NSGA-II)

The central idea of the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) (DEB *et al.*, 2002), also known as Elitist NSGA-II, is to find a set of non-dominated individuals in relation to the rest of the population and considers that this set has the highest level of dominance. Then repeat the same procedure with the rest of the population, separating it at various levels of non-dominance. Thus, Deb *et al.* (2002) state NSGA-II has an explicit diversity preservation mechanism, and elitism does not allow an already found Pareto optimal solution to be deleted.

NSGA-II emerged as an improved version of NSGA (SRINIVAS; DEB, 1994). The traditional NSGA algorithm has some differences about a simple genetic algorithm (GA) since the solutions are classified based on their dominance information. That is, for each solution, the non-dominance of this solution (number of solutions that dominate it) and the set of solutions dominated by it is calculated (COELLO, 2006). Thus, a ranking is made based on the non-dominance relationship (KUNWAR; YASH; KUMAR, 2013; SRINIVAS; DEB, 1994).

In addition to non-dominance, the NSGA-II calculates the mean distance between the solutions along each objective function to obtain the density of solutions that involves each solution present in the population – crowding distance (COELLO, 2006), a factor that favors the solutions that are better distributed along the non-dominance frontier or Pareto frontier (PF), preserving the diversity of the solutions and avoiding a possible premature convergence for a good location (KUNG; LUCCIO; PREPARATA, 1975; MIETTINEN, 1999).

Thus, the first step of the NSGA-II is the initialization of a population ($P_{t=0}$), with random size N_{pop}. Next, the selection, crossover, and mutation operators are applied to generate a daughter population $Q_{t=0}$, also of size N_{pop}. Then an auxiliary population $R_{t=0}$, with size $2N_{pop}$, is made by joining the two populations. This auxiliary population is then sorted by dominance levels, and then the frontier individuals at each level are inserted following an increasing order of levels in the new population P_{t+1} until it reaches the size N_{pop}. If the boundary of the last level to be inserted has more individuals than necessary to complete the new population of size N_{pop}, an ordering of the individuals of this level by agglomeration distance is carried out. Only the best individuals of this last level, sufficient to complete the size of the new population, will be inserted (DEB *et al.*, 2002).

The remaining individuals from the last level will be discarded along with the rest of the individuals that were not entered into the new population. The new population P_{t+1} undergoes a selection, crossing, and mutation so that it gives rise to its offspring, Q_{t+1}. The process continues until the stopping conditions are reached. At the end of the algorithm, the individuals of the first level of dominance represent the solution for the problem (DEB *et al.*, 2002). Figure 10 illustrates the necessary procedure of the NSGA-II optimization technique.

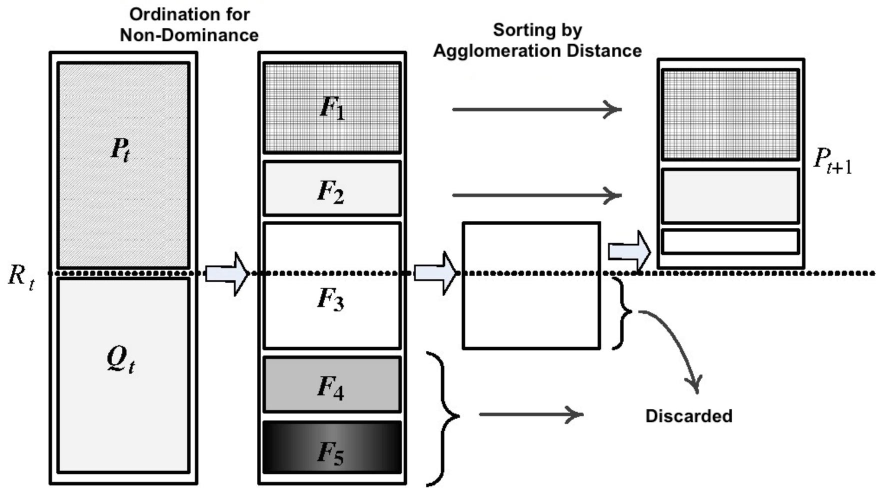

Figure 10 – NSGA-II Selection Procedure.
(DEB *et al.*, 2002)

2.5 Related Work

Demand response programs aim to balance the supply and demand of electricity. Consumers who participate in the DR programs are, according to (SIANO, 2014), able to modify their energy consumption by using load reduction strategies as well as using non-peak periods to reduce their overall energy consumption. However, the utilities must be aware of their consumer behaviour profiles in order to establish changes in electricity prices as well as prepared for any threats that could occur to the system reliability (VARDAKAS; ZORBA; VERIKOUKIS, 2015).

Demand response programs have successfully reduced costs and consumption of commercial and industrial consumers, according to Setlhaolo, Xia and Zhang (2014), but not for residential consumers as there is a need for manual intervention by residential consumers concerning the use of their home appliances. In general, the consumer does not want to be involved in such EPS-related programs, which consequently prevents the setting up of DRPs in a residential setting. Also as stated by Roh and Lee (2016), there are many appliances in each residence each with its energy consumption and operational characteristics. Consequently, there is a need to compute the energy consumption and characteristics of each appliance in a DR problem.

Due to the importance of DR in the current scenario, which is heading towards a possible energy crisis, this issue has been analyzed by various scientific researchers in order to propose optimization mechanisms for the management of residential electric energy consumption in Smart Grids. This work reviews each scientific proposal according to the type of tariff model used (TOU, RTP, CPP) and also details aspects, such as the objective and the product of the research; the optimization method; the contributions; and its limitations. The literature on the development of optimization processes to manage residential electric energy consumption using price-based DR programs can be categorized into:

2.5.1 Time-Of-Use Pricing

The Time-of-Use (TOU) optimization process has been extensively studied to solve residential DR-related problems, considering the schedule of home appliances, which improves energy consumption efficiency.

Silva, Khan and Han (2018) presented a smart home energy management system that reduces unnecessary energy consumption by integrating an automated switching off the system with load balancing and appliance scheduling algorithm. The proposal for minimizing the cost of energy was developed as a mixed-integer programming problem. The scheduling of appliances adheres to the least slack time (LST) algorithm while considering user comfort during scheduling. The results of the computational simulations show that the LST-based energy management scheme reduces the cost associated with the consumption of electricity. However, the work does not contemplate the different categories of appliances in the optimized scheduling of use of the home appliances.

Mahapatra, Moharana and Leung (2017) showed a new method named as Home Energy Management as a Service (HEMaaS) to manage the use of home appliances. The main objective of HEMaaS is to shift and curtail household appliance usages so the peak demand and total energy consumption can be reduced. The authors formulated HEM problem as a set of discrete states, where each state represents a binary formulation of the power levels of home appliances. The Main Command and Control Unit (MCCU) issues a command to switch these power states. The power states formulated as a Markov Decision Process (MDP) and derive its solution using reinforcement learning (RL) based Neural Fitted Q-Iteration (NFQI) algorithm. However, the results of the computational simulations showed that the proposal did not consider the simultaneous use of different categories of home appliances faced with this new optimized scheduling.

An algorithm for thermostat settings to reduce electricity bills was expounded by Kamyar and Peet (2017). The thermostats settings were desenvolved as dynamic programming (DP) problem. Kamyar and Peet (2017) use a Partial-Differential Equation (PDE) model of thermal diffusion to create an algorithm which determines the thermostat settings which minimize the electricity bill for a consumer with both TOU and demand charges. The algorithm was able to reduce the electricity bills by up to 25% in the summer which was 9.2% over other models using data from the Arizona utility Salt River Project (SRP). However, the proposal only evaluated thermal appliances without considering the different categories of home appliances.

A load control for optimal residential DR was performed by Wang and Paranjape (2017a). The proposal aimed to minimize electricity payments and waiting time and was designed as linear programming (LP) problem. A software home agent (HA) is designed to predict and control electricity loads. The results of the proposal showed that the peak-to-average power ratio (PAR) and electricity bills were significantly reduced. Moreover, the models and the control mechanism can be set up in a residential energy management system (EMS) for decision making for homeowners responding to the DR policies.

An electricity load scheduling algorithm was also propounded by Roh and Lee (2016), which controlled the operational times and energy consumption levels of the home devices. The loads were managed as mixed integer nonlinear programming (MINLP) problem. The authors used the Benders decomposition approach to solve the problem with low computational complexity. Therefore this algorithm was more flexibility than other algorithms, and the balance between satisfaction (use of equipment) and cost can be controlled by the consumer. Moreover, the algorithm can be applied to any appliance. In this case, the proposal was restricted to only one residence.

Setlhaolo, Xia and Zhang (2014) implemented an optimization model with the time-of-use electricity tariff where the main goal was a cost reduction linked to consumption, and it was developed as a mixed integer nonlinear programming problem. The formulated model is solved with AIMMS software, which uses Aimms Outer Approximation Algorithm (AOA) that utilizes CPLEX and CONOPT as mixed integer programming (MIP) and nonlinear programming (NLP) as solvers respectively. The model, differently from other standard models, considered the inconvenience level of appliance programming. However, by moving consumption to off peak periods linked to varying prices and incentives the model can obtain a 25% saving or more. The computational simulations of this work only used a sampling time interval of 10 minutes and a single residence containing ten residential apparatuses. Thus, this proposal did not consider in the computational simulations the different categories of home appliances.

Asare-Bediako, Kling and Ribeiro (2013) lodged a multi-agent based architecture for optimal energy management in smart homes. Four optimization strategies – comfort, cost, green (energy-efficient) and smart (demand side management) - are proposed and explained. The household devices are modelled in MATLAB, and the JAVA/JADE platform is used for the agent design and communication. However, the proposal restricts itself to evaluating only the washing machine, dishwasher, heat pump and PV system without considering the different categories of home appliances. Moreover, consider only the level of satisfaction and comfort of home owners in relation to thermal comfort.

Ozturk *et al*. (2013b) broached a DR System for residential loads within the consumer comfort zone. The system predicts the consumption and informs the utility of the demand in order to optimize consumption. The scheduling of the operation of residential appliances was developed as a non-convex programming problem. The proposed energy management solution learns and adapts to the residential energy usage patterns. The adaptive neuro-fuzzy learning algorithm developed makes DR decisions based on the following factors: 1) peak load forecast, 2) differential electricity prices, 3) customer’s usage patterns and energy budget, 4) social and environmental factors, and 5) available solar power. The proposal supplies a system that optimizes the running times of the appliances and reduces the price of the electricity consumed. However, incorrect settings made by the consumer may introduce higher costs. Moreover, this proposal was limited to seven home appliances and did not consider the different categories involved.

Pipattanasomporn *et al.* (2012) conceived an algorithm to manage the residential loads, to reduce the total consumption of electric energy considering the preferences of the consumers. Also, the authors presented a simulation tool in C++ that was developed to simulate DR events to exemplify the applicability of the proposed algorithm. However, the proposal restricts itself to evaluating only the air conditioners, water heaters, clothes dryers, and electric vehicles without considering the different categories of home appliances.

An electricity load algorithm was proposed by Lee and Lee (2011) to schedule and control each appliance regarding operational time and energy consumption. The aim of this load algorithm is to minimize residential electricity bills. The proposal was developed as a convex programming problem. The algorithm successfully reduced residential electricity bills by re-scheduling the operational times of the domestic appliances taking into consideration their specific operational and energy consumption characteristics. However, the authors only included four home appliances in the program without considering their different categories.

A scheduling framework, which models decision problems, was built by Sou *et al.* (2011). The scheduling framework, designed as a mixed integer linear programming (MILP) problem, solves configuration problems related to different home appliances considering the tariffs. The MILP scheduling problem is solved using CPLEX (using the YALMIP MATLAB interface). Thus, The proposal can reduce 47% of the cost of electricity, and it can be used with renewable energy, storage batteries and to optimize energy consumption and CO_2 emissions. However, it only considers the satisfaction and comfort level of the home owners.

TOU is a rate that provides various electricity pricing in different time periods such as daylight hours, weekdays and weekends. It is commonly predetermined with months or years in advance becoming it static throughout the application period. Yudong Tang *et al.* (2005) state TOU can occasion a few problems, such as: consumers do not respond immediately to the pricing because its lack of knowledge and experience; peak time may become a period of lower consumption and vice versa due to large consumer responses (TOU rate at an unreasonable price); energy utilities may have reductions in their profits by purchasing electricity at a certain price and selling it at a lower rate determined by the TOU pricing. Under these circumstances, it is necessary to analyze the applicability of other rates in the load scheduling process.

2.5.2 Real-Time Pricing

According to Lujano-Rojas *et al.* (2012), the Real-Time Pricing (RTP) allows the price of electricity to change hourly over the time horizon, thus reflecting the real cost of electricity. Consequently, many recent scientific research projects aim to implement optimization processes to reduce the consumption and electric bill of the consumers.

Lin and Hu (2018) proposed a constrained Particle Swarm Optimization (PSO)-based residential consumer-centric load-scheduling method. The proposal was developed as linear programming (LP) problem. The main objective of the work is to shift load profiles by home appliances as well as cut down on peak energy demands through a new constrained swarm intelligence-based residential consumer-centric DSM method. The swarm intelligence, constrained PSO, is used to minimize the energy consumption cost while considering users' comfort satisfaction for DR implementation. However, the proposal only evaluated the programming of nine appliances in a household. Thus, the proposal does not consider the different categories of home appliances.

Prajwal and Gupta (2018) produced a smart home energy management system to detect the peak times or supply power shortage times and do the necessary action so that the consumer does not face any issue. The system as a whole consists of two modules, a load forecasting module which will forecast the next day load of the smart home and an energy control module which will accept the inputs that are required for the continuous power supply during a power failure with also economic utilization of the energy. The smart home energy management system takes into consideration the nonlinear system of inputs and takes action in supplying the electrical energy continuously while also reducing the cost. The developed fuzzy logic system is tested for the various conditions of the input in the MATLAB/Simulink environment with the varying input such as electricity price of the day, load forecasted from the energy control module, state of charge level in the battery and the supply power availability.

However, the results of the computational simulations showed that the proposal did not consider the simultaneous use of different categories of home appliances nor the level of satisfaction and comfort of the consumers faced with this new optimized scheduling.

Nizami and Hossain (2017) displayed an optimal scheduling model for Demand Response (DR) based Home Energy Management System (HEMS) that schedules residential electrical appliances and Distributed Energy Resource (DER) units for active residential consumers. The proposal was designed as a mixed-integer linear programming (MILP) problem and aims to minimize the electricity expenditure of the consumer while maintaining an optimal comfort level. MATLAB optimization toolbox is used to develop the MILP-based scheduling model. The proposed HEMS model is simulated and verified with a case study for a typical house, and the simulation showed positive results with up to 18% energy expenditure savings for the consumer. However, the authors restrict themselves to only evaluating one residential unit, and the proposal only evaluated four devices without considering the different categories of home appliances.

A multiagent system was introduced by Wang and Paranjape (2017b) to manage a residential DR program. The aim was to reduce the peak-to-average ratio (PAR) as well as the final costs. The consumption control is made into a convex programming problem and can thus minimize the cost of electricity under real-time pricing. However, only the satisfaction and comfort levels regarding electric vehicle recharging schedules were considered.

Zhang *et al.* (2016) produced a decoupled DR strategy and an interdisciplinary mechanism that integrates machine learning in artificial intelligence, optimization in mathematics, and data structure design in computer science to develop DR and HEM systems. The loads (HVAC and deferrable) scheduling problem can be solved separately through linear or nonlinear programming method for HVAC and binary integer programming technique for deferrable loads providing a final optimal solution. Thus, this work has as main objective is to develop an integrative and adaptive demand response and HEM system considering variable and real-life conditions. Therefore, according to the authors, the proposed DR and HEM technique can be adaptive to real-life weather, seasonal, and house condition changes. Furthermore, the work did not evaluate the impact of modifying the programming of different categories of home appliances on the satisfaction and comfort of the consumers.

Reballo and Casella (2016) showed a mobile application to remotely manage the home appliances operation. The proposal aims to handle different residential appliances to reduce the cost associated with electricity consumption. The load schedule is formulated as a constrained optimization problem. Thus, it is based on genetic algorithms (GA) to solve the load scheduling problem. However, it does not include in its formulation the different categories of home appliances. Also, the proposal is restricted to evaluate only the refrigerator, batteries, air conditioning, pump, and electric stove.

Jovanovic, Bousselham and Bayram (2016) suggested a new demand response scheduling framework for an array of households, which are grouped into different categories based on socio-economic factors, such as the number of occupants, family decomposition and employment status. The proposal considers the preferences of participating households and aims to minimize the overall production cost and, in parallel, to lower the individual electricity bills. The proposal was mathematically designed as a mixed integer programming problem. The model was implemented using IBM ILOG CPLEX and executed using the default solver settings. The computational simulations showed that coupling the preference levels of the consumers with the associated job descriptions can be beneficial, for both the customer and the utility company. The results also showed that the reduction in the operations of the utility company could also be reflected in customer bills using incentives. A significant level of savings in production costs can be achieved while maintaining a high degree of satisfaction for the participating households. Also, further savings can be achieved by allowing a higher level of maximal dissatisfaction for households. However, the work presented does not consider the different categories (interruptible and deferrable, uninterruptible and deferrable, uninterruptible and non-deferrable) of home appliances.

Muratori and Rizzoni (2016) broached a dynamic energy management framework based on energy consumption models. The optimal control problem is solved using dynamic programming, finding the global solution that minimizes a cost function. The algorithm is general, and different cost function could be selected to achieve different objectives. Simulation results show that the modelling proposed in this paper can serve as a tool to study energy policy solutions, including evaluating and comparing the effects of different electricity price structures and developing effective residential demand response programs. However, the work did not evaluate the impact of modifying the programming of different categories of home appliances on the satisfaction and comfort of the consumers.

An algorithm for a Home Energy Management Scheduler (HEMS) that could manage residential energy consumption to reduce the electricity bill was built by Vivekananthan, Mishra and Li (2015). Stochastic dynamic programming was developed to manage the home appliances. Thus, the Markov decision process (MDP) is used to minimize the cost of energy consumption by predicting the appropriate curtailment of appliances based on the stochastic behaviour of the cost of consumption. The work only evaluated the programming of seven home appliances and did not consider the impact of modifying the programming of different categories of home appliances on the satisfaction and comfort of the consumers.

Oladeji and Olakanmi (2014) conceived an approach to minimize the overall cost of electricity payment. The residential load management approach is formulated as a constrained optimization problem and to solve the optimization problem was used Genetic Algorithms (GA). The results confirm that GA can optimize energy consumption, thus minimizing overall electricity cost for ends consumers. However, in the computational simulations, the authors only included five home appliances without considering the different categories of these appliances.

Samadi *et al.* (2014) established two interactive algorithms based on the stochastic approximation technique to minimize peak-to-average ratio (PAR) in aggregate load demand. The proposal was developed as mixed-integer linear programming (MILP) problems and to solve the optimization problem was used software MOSEK. The authors also proposed the use of a system simulator unit (SSU) that employs approximate dynamic programming to simulate the operation of the ECS devices and users' price-responsiveness. However, the results of the computational simulations show that the algorithms do not consider the simultaneous use of different categories of home appliances and the level of satisfaction and comfort of the consumers faced with the optimized scheduling of such home appliances.

Nair and Rajasekhar (2014) devised a DR algorithm to control energy consumption. The DR algorithm is formulated as a linear programming (LP) problem with an objective to minimize the cost of electricity consumption on the customer side or maximize the profit on the utility side. The proposal aimed to modify the residential electricity consumption profiles considering the daily price of electricity and the preferences of consumers regarding the use of home appliances. The optimization problem is modelled in MATLAB and solved using GUROBI-MATLAB interface. However, the proposal restricted itself to evaluating only five consumers with a single standard of consumption and seven home appliances.

Zhou *et al*. (2014) exhibited a system to manage the consumption of residential electricity in real time. The approach was developed as a mixed integer programming (MIP) problem and can deal with complex operational environments and thus reduce costs associated with consumption. The problem is solved by combining hour-ahead (half-hour or 15 min) rolling optimization (RO) over the next 12 or 24 hours and the real-time control strategy (RTCS) for each minute. The economic dispatch of controllable loads can be achieved by the hour-ahead scheduling. The real-time control speed is ensured by the practical control strategy. However, different categories of home appliances were not included.

A New Traversal-and-Pruning (TP) algorithm for thermostat schedules for load control was designed by Wang *et al.* (2013a). The aim was to reduce costs and increase consumer comfort. It was developed as a mixed integer nonlinear programming problem. The new TP algorithm had a better performance than existing ones considering: optimization, robustness, speed, and flexibility to solve commitment issues. Also, it can be applied in home and building energy management systems, thus optimizing device load schedules. Moreover, it helps consumers set up optimal load schedules with lower cost and higher comfort. However, this work only evaluated the programming of thermal devices, such as electric water heaters (EWH).

An approach to managing residential loads to reduce costs and the peak-to-average ratio (PAR) by scheduling operations was assembled by Zhao *et al.* (2013). The proposal was developed as a nonlinear programming problem and to solve the optimization problem was used as a genetic algorithm (GA). However, only nine types of home appliances were considered, and only sixteen operations per planning horizon were considered, and these must be programmed by the consumers.

A demand management approach, which was developed as a nonlinear programming problem, to manage different categories of home appliances simultaneously was made by Logenthiran, Srinivasan and Shun (2012). The objective of the proposal is to schedule the operation of the home appliances in order to bring the final load consumption curve as close as possible to the curve obtained from the goal defined by the energy utility, in order to achieve the desired management strategy. However, the proposal does not include in the simulations computational the different categories (interruptible and deferrable, uninterruptible and deferrable, uninterruptible and non-deferrable) of home appliances.

In Chen, Wu and Fu (2012), a real-time DR management model is exposed in order to assist end consumers in the automatic operation of their home appliances. The scheduling of the home appliances is managed as a whole mixed-integer linear programming (MILP) problems. The stochastic optimization adopts the scenario-based approach via Monte Carlo (MC) simulation for minimizing the expected electricity payment for the entire day, while controlling the financial risks associated with real-time electricity price uncertainties via the expected downside risks formulation. Price uncertainty intervals are considered in the robust optimization for minimizing the worst-case electricity payment while flexibly adjusting the solution robustness. However, the results of the computational simulations show that the proposal is limited to evaluating the programming of only six home appliances without considering the different categories of these apparatuses.

In Du and Lu (2011), a new appliance commitment algorithm that schedules thermostatically controlled appliances (TCAs) based on price and consumption forecasts in real time was implemented. The energy consumption scheduling problem is formulated as a nonlinear optimization problem that aims to minimize the electricity payment subject to the user-comfort constraint. However, this work only evaluated the programming of thermal devices without considering the different categories of home appliances.

Conejo, Morales and Baringo (2010) presented a real-time DR model developed as linear programming (LP) problem, using the robust optimization technique to model changes in the price of electricity. The aim of the proposal is to adjust load levels in response to hourly electricity price changes, leading the residential consumer to use as little electricity as possible but not considering the inconvenience caused to him. The proposal also does not consider the different categories of home appliances and the individualized representation of loads, which implies an optimal solution to the problem that is not feasible in a real scenario.

In Mohsenian-Rad and Leon-Garcia (2010), a framework was devised to optimally schedule household appliance operations which aims to achieve a trade-off between minimizing the payment and minimizing the waiting time for the operation of each household appliance. The scheduling of the home appliances is managed as whole linear programming (LP) problem and to solve the optimization problem was used interior-point method in polynomial computation time. Simulation results show that the combination of the proposed energy scheduler design and the price predictor leads to significant reduction in users' payments. This encourages the users to participate in the proposed residential load control program. However, the proposal does not include in the simulations computational the different categories of home appliances.

The RTP rate offers electricity prices that change every hour reflecting the variations of wholesale market prices. Thus, unlike the TOU that presents static values for electricity, RTP warns consumers of the price of electricity with hours or day in advance. Therefore, RTP it allows to offer the greatest feedback to end consumers in relation to the potential savings in the electricity bill (AZEVEDO; FLORA, 2017).

2.5.3 Critical-Peak Pricing

Critical-Peak Pricing (CPP) is a dynamic tariff model that uses TOU and RTP tariff elements to adjust the price of electricity in a temporary response to events or conditions, such as high market prices, network consumption peaks or decreasing reserves (WANG *et al.*, 2013b). Some research has been done to analyze the impact of the optimization process and the CPP tariff on the electric power system.

Javaid *et al.* (2017) propounded a hybrid scheme named GAPSO for residential load scheduling, to optimize the desired objective function of minimizing the electricity cost and user discomfort while considering the peak energy consumption. The GAPSO scheme was implemented and its performance compared against traditional dynamic programming (DP) technique and two heuristic optimization techniques: genetic algorithm (GA) and binary particle swarm optimization (BPSO) for residential load management. They formulated the binary optimization problem through a multiple knapsack problem (MKP). The results of the simulation showed that the proposed hybrid scheme, GAPSO, performed better regarding cost and occupant discomfort minimization along with the reduction of peak power consumption compared to its counterpart schemes GA and BPSO. However, the authors did not contemplate, in the performance analysis for the management of residential loads, the category that includes heating, ventilation, and air conditioning (HVAC) appliances. Thus, the devices with high load consumption were not analyzed.

An optimization model was illustrated by Bin *et al.* (2016) to deal with the critical peak pricing (CPP) policy. The goal, based on the fee balance mode and the fee increase mode, was to obtain the best pricing strategy for the CPP days. The proposal was designed as a mixed integer non-linear programming problem. The CPP and VP load transfer factors were assumed to have certain values; therefore, further determination and sensitivity analysis of the two parameters should be carried out.

A Critical Peak Pricing (CPP) dynamic decision-making model was developed by Yin, Zhou and Li (2015). The charging load of electric vehicles was considered in this model in order to reduce costs and the peak load. The results show that this CPP is able to reduce the peak load and the peak electricity price gradually comes down with an increase in the number of electric vehicles until reaching a stable level. However, only satisfaction and comfort levels are considered while the different categories of home appliances are not evaluated.

An optimal non-stationary DSM mechanism was expounded by Song, Xiao and Van Der Schaar (2014) to minimize the total cost and improve on the optimal stationary DSM strategy. Designed as a linear programming problem, the proposed DSM mechanism considered not only the billing costs but also the discomfort costs. It can model different discomfort costs for different consumers. However, the authors do not make it clear how the DSM proposal deals with the specific impact of the different peculiarities of the devices on the daily life of the end consumers.

Siano *et al.* (2013) introduced a new decision support and energy management system (DSEMS) for residential applications. The proposal aims to maintain the efficiency of the network both regarding the continuity of electricity supply and saving energy and economy. The DSEMS is represented as a finite state machine and implemented in Stateflow of MATLAB while the residential thermal and electrical models are implemented in Simulink of MATLAB. The DSEMS allows reducing energy costs during the economic scenario of about 18%, while in the case of the comfort scenario the user comfort is preserved. However, the proposal restricts itself to evaluating only the air conditioners, lights, dishwasher, washer and dryer without considering the different categories of home appliances.

A decision-support tool proposed by Pedrasa, Spooner and Macgill (2010) aims to optimize the energy services for residential consumers. This is carried out by scheduling the operation of available distributed energy resources. The schedule for the distributed energy resources (DER) maximizes the net benefit coming from the services. The net benefit is the total benefits less the energy costs. The proposal was developed as a stochastic programming problem. The main difference of this tool is that the end-users put different levels of benefit to different services at different times of the day. These benefits are used to develop the DER schedules. This approach enables the curtailment of services if the cost of provision exceeds their benefits. The results showed that the proposal was limited to four apparatuses without considering their different categories of home appliances.

CPP uses TOU as its base tariff structure but uses the TOU or RTP tariff characteristics depending on the situation in the electric power system, for example, when the network contingencies or the cost of generation are very high. However, CPP can cause problems such as not specifying the time, duration and number of days that the electricity price will be high. Thus, the CPP rate is still not widely used and, for this reason, several surveys are being conducted to verify the CPP efficiency in the home appliance usage optimization process.

Most of the recent studies presented in this thesis (NAIR; RAJASEKHAR, 2014; OZTURK *et al.*, 2013b; SAFDARIAN; FOTUHI-FIRUZABAD; LEHTONEN, 2014; VIVEKANANTHAN; MISHRA; LI, 2015; WANG; PARANJAPE, 2017a) show that the main goal is to minimize the cost associated with the consumption of electric energy without considering the preferences/needs of end consumers. Therefore, we can say that these works do not consider the real difficulty of the problem which involves scheduling the use of home appliances and they do not evaluate aspects such as: (a) different residential scenarios; (b) various categories of home appliances; (c) the level of satisfaction/comfort of consumers with the new scheduling of their home appliances. Moreover, the studies that dealt with the inconvenience aspect performed simulations without contemplating the different categories of home appliances, thus reducing the complexity of the method.

Based on the assumption presented throughout this section, RTP pricing was adopted in the experiments performed because it is the one that best reflects the average price of electricity in the market. Besides that, RTP is the rate that offers the best feedback to the end consumer regarding the potential of reduction in the total cost related to electricity consumption as well as the reduction of financial losses for the electric utility. Table 1 shows a summary of the scientific production review. It highlights the studies developed to improve the usage of management for home appliances that apply energy efficiency through price-based DRP in smart grids.

Table 1 – Comparison Between the Related Works.

References	Description	Cost Minimization	Satisfaction/ Confort	Pricing Scheme	Problem Formulation	Technique
(ASARE-BEDIAKO; KLING; RIBEIRO, 2013)	Research Product: a multi-agent based architecture for optimal energy management in smart homes.	X	X	TOU		Software Agent
(BIN *et al.*, 2016)	Research Product: an optimization model dealing with the critical peak pricing (CPP) policy.	X		CPP	Mixed Integer Non-Linear Programming	
(CHEN; WU; FU, 2012)	Research Product: a real-time DR model to automatically schedule the operation of residential appliances of the final consumers.	X		RTP	Mixed Integer Linear Programming	Monte Carlo (MC) Simulation
(CONEJO; MORALES; BARINGO, 2010)	Research Product: an optimization model to adjust the hourly load level of a given consumer in response to hourly electricity prices.	X		RTP	Linear Programming	CPLEX
(DU; LU, 2011)	Research Product: New appliance commitment algorithm that programs the implementation of residential loads based on forecasts of price and consumption.	X	X	RTP	Non-Linear Programming	Commitment Algorithm
(JAVAID *et al.*, 2017)	Research Product: a hybrid scheme named GAPSO for residential load scheduling, to optimize the desired objective function of minimizing the electricity cost and user discomfort while considering the peak energy consumption.	X	X	CPP	Multiple Knapsack	Genetic Algorithm and Binary PSO
(JOVANOVIC; BOUSSELHAM; BAYRAM, 2016)	Research Product: a new demand response scheduling framework for an array of households, which are grouped into different categories based on socio-economic factors, such as the number of occupants, family decomposition and employment status.	X	X	RTP	Mixed Integer Linear Programming	CPLEX

(KAMYAR; PEET, 2017)	Research Product: an algorithm which determines the thermostat settings which minimize the electricity bill for a consumer.	X		TOU	Constrained Dynamic Optimization	Dynamic Programming Algorithm
(LEE; LEE, 2011)	Research Product: an electricity load scheduling algorithm that controls the operation time and energy consumption of each appliance.	X		TOU	Convex Programming	
(LIN; HU, 2018)	Research Product: a constrained Particle Swarm Optimization (PSO)-based residential consumer-centric load-scheduling method.	X	X	RTP	Linear Programming	Particle Swarm Optimization
(LOGENTHIRAN; SRINIVASAN; SHUN, 2012)	Research Product: the approach to simultaneously manage different categories of residential devices.	X	X	RTP	Non-Linear Programming	Heuristic-based Evolutionary Algorithm
(MAHAPATRA; MOHARANA; LEUNG, 2017)	Research Product: a new method named Home Energy Management as a Service (HEMaaS) to manage the use of home appliances.	X		TOU	Binary Programming	Markov Decision Process (MDP) and Neural Fitted Q-learning (NFQI) Algorithm
(MOHSENIAN-RAD; LEON-GARCIA, 2010)	Research Product: a framework was devised to optimally schedule household appliance operations which aims to achieve a trade-off between minimizing the payment and minimizing the waiting time for the operation of each household appliance.	X	X	RTP	Linear Programming	Interior-point Method in Polynomial Computation Time
(MURATORI; RIZZONI, 2016)	Research Product: a dynamic energy management framework, based on energy consumption models.	X		RTP	Dynamic Programming	
(NAIR; RAJASEKHAR, 2014)	Research Product: DR algorithm that uses electricity market prices from the power utility and consumer preferences for operating appliances.	X	X	RTP	Linear Programming	GUROBI-MATLAB Interface

(NIZAMI; HOSSAIN, 2017)	Research Product: an optimal scheduling model for Demand Response (DR) based Home Energy Management System (HEMS) that schedules residential electrical appliances and Distributed Energy Resource (DER) units for active residential consumers.	X	X	RTP	Mixed Integer Linear Programming	MATLAB
(OLADEJI; OLAKANMI, 2014)	Research Product: a residential load management approach to minimize the overall cost of electricity payment.	X		RTP	Constrained Optimization	Genectic Algorithm
(OZTURK *et al.*, 2013b)	Research Product: demand response system that programs residential loads within the consumer comfort zone.	X	X	TOU	Non-convex Programming	Adaptive Neuro-Fuzzy Learning Algorithm
(PEDRASA; SPOONER; MACGILL, 2010)	Research Product: a decision-support tool that optimizes the energy services of residential end-users by scheduling the operation of available distributed energy resources.	X		CPP	Stochastic Programming	Coevolutionary Particle Swarm Optimization
(PIPATTANASOMPORN *et al.*, 2012)	Research Product: an algorithm to manage the residential loads, to reduce the total consumption of electric energy considering the preferences of the consumers.	X	X	TOU		C++
(PRAJWAL; GUPTA, 2018)	Research Product: a smart home energy management system to detect the peak times or supply power shortage times and do the necessary action so that the consumer does not face any issue.	X		RTP	Non-linear Programming	Fuzzy Logic
(REBALLO; CASELLA, 2016)	Research Product: a mobile application to remotely manage the home appliances operation.	X		RTP	Constrained Optimization	Genetic Algorithm
(ROH; LEE, 2016)	Research Product: an electricity load scheduling algorithm.	X	X	TOU	Mixed Integer Non-linear Programming	Benders Decomposition Approach
(SAMADI *et al.*, 2014)	Research Product: two interactive algorithms based on the stochastic approximation technique to minimize	X		RTP	Mixed Integer Linear	MOJEK Software

	peak-to-average ratio (PAR) in aggregate load demand.				Programming	
(SETLHAOLO; XIA; ZHANG, 2014)	Research Product: a practical optimization model based on a time-of-use electricity tariff for a household.	X	X	TOU	Mixed Integer Non-linear Programming	AIMMS Software
(SIANO *et al.*, 2013)	Research Product: an energy management system (DSEMS) for residential applications	X	X	CPP	Linear Programming	MATLAB
(SILVA; KHAN; HAN, 2018)	Research Product: a smart home energy management system that reduces unnecessary energy consumption by integrating an automated switching off the system with load balancing and appliance scheduling algorithm.	X	X	TOU	Mixed Integer Linear Programming	Least Slack Time (LST) Algorithm
(SONG; XIAO; VAN DER SCHAAR, 2014)	Research Product: an optimal nonstationary DSM mechanism.	X	X	CPP	Linear Programming	N-DSM Algorithm
(SOU *et al.*, 2011)	Research Product: a scheduling framework that models decision problems as realistically as possible.	X		TOU	Mixed Integer Linear Programming	CPLEX
(VIVEKANANTHAN; MISHRA; LI, 2015)	Research Product: an algorithm for a Home Energy Management Scheduler (HEMS) to manage the consumption of residential electrical energy.	X		RTP	Stochastic Dynamic Programming	Markov Decision Process (MDP)
(WANG *et al.*, 2013a)	Research Product: New Traversal-and-Pruning (TP) algorithm to program thermostat schedules for residential load control.	X	X	RTP	Mixed Integer Non-linear Programming	Traversal-and-Pruning (TP) Algorithm
(WANG; PARANJAPE, 2017a)	Research Product: a load control model for optimal residential DR implementation.	X	X	TOU	Linear Programming	Software Agent
(WANG; PARANJAPE, 2017b)	Research Product: a multiagent system to manage residential DR.	X	X	RTP	Convex Programming	Software Agent
(YIN; ZHOU; LI, 2015)	Research Product: a Critical peak pricing (CPP) dynamic decision-making model.	X	X	CPP	Dynamic Programming	Particle Swarm Optimization

(ZHANG *et al.*, 2016)	Research Product: a decoupled DR strategy and an interdisciplinary mechanism to develop DR and HEM systems.	X		RTP	Linear e Non-linear Programming for HVAC and Binary-Integer Programming for Deferrable Loads	Machine Learning, Optimization Mathematics, and Data Structure Design
(ZHAO *et al.*, 2013)	Research Product: an approach to manage residential loads.	X		RTP	Non-Linear Programming	Genetic Algorithm
(ZHOU *et al.*, 2014)	Research Product: an approach to manage the consumption of residential electricity.	X		RTP	Mixed Integer Linear Programming	Rolling Optimization Algorithm

Chapter 3

HOME ENERGY MANAGEMENT SYSTEM (HEMS)

In this chapter, the Home Energy Management System (HEMS) architecture is shown in detail as well as the DR optimization model, which aims to determine the optimum programming of residential appliances. Thus, the various restrictions associated with energy consumption are explained here, such as the minimum and maximum limits of the load for each time interval; ramp limits; minimum consumption related to the time horizon; and operational restrictions of the home appliance categories.

3.1 Initial Considerations

The Home Energy Management System (HEMS) can include any product or service that monitors, controls and analyzes the electrical energy of a home. According to Khan *et al.* (2015), a HEMS incorporates residential utility demand response programs, home automation services, personal energy management, data analysis and visualization, auditing, and related security services.

The HEMSs have been operating for decades, and their main function is to optimize, monitor and control the flow of electricity (ERTUGRUL; MCDONALD; MAKESTAS, 2017; KHAN *et al*., 2015). Thus, this thesis proposes a HEMS that aims to solve a DR problem involving the minimization of the cost related to the electricity consumption and the inconvenience level for end consumers through the home appliance optimized programming. Therefore, the Energy Management Controller (EMC) of HEMS was implemented through the DR optimization model using different optimization techniques (Genetic Algorithm (GA), Particle Swarm Optimization (PSO) Language for Interactive General Optimizer (LINGO) and Non-dominated Sorting Genetic Algorithm II (NSGA-II)) in order to (re)schedule the loads of home appliances, considering the real-time pricing of electricity and the satisfaction/comfort of consumers.

3.2 Architecture of HEMS

Home Energy Management System is defined as the system that provides power management services in order to efficiently monitor the generation, storage and consumption of electricity in smart homes. Therefore, HEMS consists of demand response programs, automation services, power management, data visualization/analysis, auditing and security services (ZHOU *et al.*, 2016).

Home Energy Management System provides bidirectional communication between homes and the electric utility to monitor, control and analyze the data that involves the consumption of electricity in smart homes (ZHOU *et al.*, 2016). The communication technologies, Wide Area Network (WAN), Neighborhood Area Network (NAN) and Home Area Network (HAN) (KUZLU; PIPATTANASOMPORN; RAHMAN, 2014; YE; QIAN; HU, 2015; ZHOU *et al.*, 2016) used in the smart grid serve as the basis for the HEMS as proposed in this work.

The HEMS proposed in this work is basically composed of an advanced metering infrastructure (AMI), a smart meter (SM), an energy management controller (EMC) and the home appliances. This HEMS architecture is presented in Figure 11.

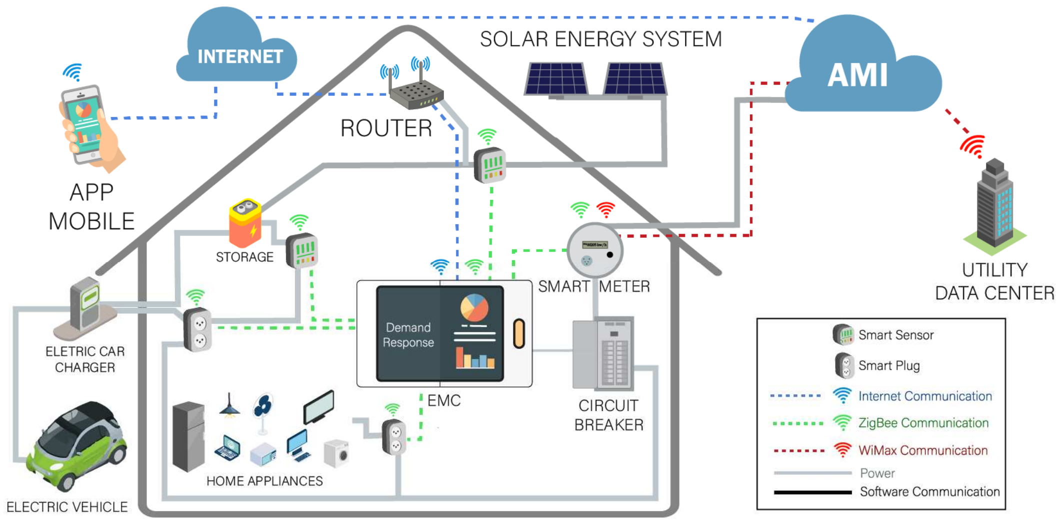

Figure 11 – Illustration of home energy management system (HEMS) architecture. (VERAS *et al.*, 2018a)

The smart meter is equivalent to a communication interface and is usually mounted between the AMI and EMC in order to collect the electrical energy consumption data from each device using ZigBee (IEEE 802.15.4) technology (RAMYA; SHANMUGARAJ; PRABAKARAN, 2011) and it also receives the price of electricity from the utility company in real time.

The AMI provides intelligent bidirectional communication between the SM and the utility company. This enables automated measurement functions and also enables the utility company to send real-time data on energy consumption and price. The information is transmitted or received from the utility company through commonly available fixed networks such as PLC (Power Line Communication), GSM (Global System for Mobile Communications) or WiMax (KABALCI, 2016; SIANO, 2014). Thus, this data can be used for further analysis such as each consumer’s demand for energy in a specific area or the schedules with the lowest electricity prices that can be used for moving loads.

The EMC is considered the operating nucleus of the home network and is responsible for the management of the consumption and production of energy. Based on this, the proposed HEMS can manage various devices such as electric vehicles, electrical energy storage systems, renewable energy generation, and home appliances. HEMS uses an algorithm to allow consumers to monitor and/or reschedule the configurations of the existing devices in residence according to their needs and the DR data provided by the AMI, received via the smart meter.

The integration of multiple technologies combined with the optimized control of the EMC enables intelligent decision making, reliability, and security. An application of this architecture envisages that the generated and stored electricity can be used over a time horizon to charge not only electric vehicles but also to provide loads to the other residential devices when, for example, the cost of electricity is high. Also, HEMS communications infrastructure enables the consumers to participate actively. This is because consumers can access the whole process of monitoring, controlling and managing household energy through an Internet Mobile App. Consumers, with a HEMS Mobile App, can obtain information about energy consumption, demand and price of electricity for a certain interval of time via the SM. Thus, consumers can decide to intervene or not in the optimized programming as suggested by the EMC.

3.2.1 Energy Management Controller (EMC)

This work proposes an EMC that aims to minimize the cost associated with the consumption of electricity and the level of inconvenience (dissatisfaction/discomfort) of consumers as well as to guarantee the stability and safety of the EPS. Figure 12 shows the communication between the EMC and the different devices used in the residential load management process.

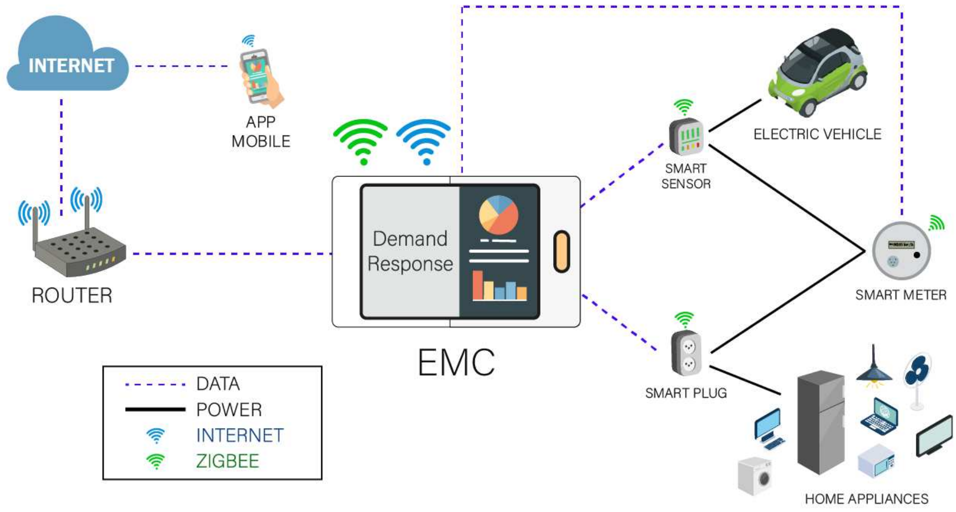

Figure 12 – Model of an EMC communication system.

(VERAS *et al.*, 2018a)

In HEMS, EMC has an essential role because it manages all home appliances through the multi-objective DR model of this work and the ZigBee communication technology involved in switching gadgets on/off. The EMC schedules all operations based on energy consumption records, the real-time electricity price, and client preferences. In this work, the residential appliances are divided into three classes (CHEN; WU; FU, 2012) as follows: interruptible and deferrable; uninterruptible and deferrable; and, uninterruptible and non-deferrable. Uninterruptible indicates that an operation cannot be interrupted until it has finished. Non-deferrable and Deferrable refer to whether an operation may start at the first time slot of the operational window, or not.

Home Energy Management System makes it easier to control and manage home appliances, to reduce the electricity consumption costs, the level of inconvenience associated with the use of appliances and it results in a lower peak-to-average ratio, which contributes to improving the reliability of the EPS operation. The multi-objective DR model used by the EMC to manage the residential appliances is presented below.

3.2.1.1 Optimization Model

The multi-objective DR optimization model presented in this thesis was formulated as a nonlinear programming problem, which considers the constraints related to electricity consumption, such as, minimum and maximum load limits for each time interval; ramp limits; minimum consumption of electric energy related to the time horizon; and the aspects associated with the inconvenience level for end consumers considering the operational restrictions of the home appliance categories. The mathematical formulation of the multi-objective model is presented as follows:

Indexes and Sets:

The indexes and sets of the multi-objective DR optimization model are:

$\boldsymbol{i}$	Index for appliance
$\boldsymbol{t}$	Index for sub-interval
$\boldsymbol{N}$	Set of indexes of all home appliances
$\boldsymbol{T}$	Set of indexes of all sub-intervals in the entire scheduling time interval
$\boldsymbol{A_I}$	Set of indexes of the appliance categories interruptible and deferrable
$\boldsymbol{A_{II}}$	Set of indexes of the appliance categories uninterruptible and deferrable
$\boldsymbol{A_{III}}$	Set of indexes of the appliance categories uninterruptible and non-deferrable

Constants:

The problem constants are:

$\boldsymbol{d^{min}}$	Minimum demand for the load levels at each time interval t
$\boldsymbol{d^{max}}$	Maximum demand for the load levels at each time interval t
$\boldsymbol{r^D}$	Ramping down limits for the time interval t
$\boldsymbol{r^U}$	Ramping up limits for the time interval t

Variables:

The variables used for modelling the DR problem and the decision variable needed to manage the home appliance operations are:

$\boldsymbol{e_i}$	Represents the vector for the energy consumption of home appliances i when in operation
$\boldsymbol{pr_t}$	Price of electricity at time t
$\boldsymbol{p_i}$	Vector with the power (in kW) of each home appliance
$\boldsymbol{mdc}$	Minimum daily consumption
$\boldsymbol{q}$	The initial time slot of the interval that will be checked if the category A_{II} home appliances were used without interruption
$\boldsymbol{ST_i}$	The start time of the operation
$\boldsymbol{ET_i}$	End time of the operation

$\boldsymbol{Req_i}$ Required time for appliance i to finish its operation

Baseline$_{t,i}$ is a variable designed as a matrix. It is the real electricity consumption in the time interval *t* for the home appliance *i* of the family analyzed by the Load Profile Generator (LPG) tool (PFLUGRADT, 2016). It can be defined as follows:

$$baseline_{t,i} = \begin{cases} 1, if\ home\ appliance\ i\ is\ on\ at\ time\ t, \\ \qquad\qquad\qquad 0, otherwise. \end{cases}$$

The $DSA_{t,i}$ displays the decision variable of the model that correspond to the load programming matrix, as follows:

$$DSA_{t,i} = \begin{cases} 1, if\ home\ appliance\ i\ is\ on\ at\ time\ t, \\ \qquad\qquad\qquad 0, otherwise. \end{cases}$$

The multi-objective DR optimization model presented in this thesis has two minimization functions: f_1 and f_2. The first one (f_1) aims to minimize the electricity consumption costs and the second (f_2) to minimize the level of the inconvenience of end consumers in relation to the optimized planning of residential loads provided by the utility.

Thus, the minimization of the energy consumption cost f_1 is formulated as follows:

$$Minimize \sum_{i=1}^{N} e_i \sum_{t=1}^{T} (pr_t\ .DSA_{t,i})^2 \tag{12}$$

Equation (12) calculates the cost associated with the consumption of electricity for each consumer, considering the number of home appliances N and the time horizon T. The first term of the equation $\sum_{i=1}^{N} e_i$ uses the energy consumption vector e of each apparatus i which is multiplied by the second term $\sum_{t=1}^{T}\left(pr_t\ .DSA_{t,i}\right)^2$. Therefore, the second term calculates the amount to be paid for each appliance i, running in time interval t. Thus, the product of the two terms gives the cost associated with the consumption of electric energy to be paid as suggested by the $DSA_{t,i}$ matrix.

Objective function f_2 aims to minimize the inconvenience and evaluate how the optimized scheduling of home appliances can modify the satisfaction/comfort of the end consumer and is given by

$$Minimize \sum_{t=1}^{T} \sum_{i=1}^{N} (baseline_{t,i} - DSA_{t,i})^2 \quad (13)$$

Accordingly, the f_2 calculation compares the real electricity consumption (*baseline*) in the time interval *t* for the home appliance *i* of the family analyzed by the Load Profile Generator (LPG) tool (PFLUGRADT, 2016) and the $DSA_{t,i}$ consumption, which is the consumption suggested by the optimization technique, and which was used in the computational simulations. The LPG is a modeling tool for residential energy consumption and it performs a full behavior simulation of the people in a household which it uses to generate load curves (PFLUGRADT, 2016).

The objective function f_2 illustrated in Equation (13), evaluates the difference between the real consumption ($baseline_{t,i}$) and the suggested ($DSA_{t,i}$) for each time interval *t*, for each home appliance *i* considered in the problem and shows how much the consumption suggested by the optimization technique distances itself from the actual consumption pattern of the family under analysis. Therefore the optimal solution will be the one that will affect the usage of the home appliances the least, while at the same time reducing the cost of electricity consumed. The smaller the difference between the normal consumption and the one suggested by the optimization technique, the better this solution will be.

The f_1 and f_2 objective functions are subjected to different constraints detailed as follows:

Constraints for f_1 objective function:

Constraint 1 (14) establishes the limits (minimum and maximum) for the load levels at each time interval *t* where $p_i(i=1,...,N)$ is the vector with the power (in kW) of each home appliance. This constraint aims to guarantee that the electricity consumption per hour does not violate the minimum/maximum limits established by the utility.

$$d_t^{min} \leq \sum_{i=1}^{N} DSA_{t,i} \;.\, p_i \leq d_t^{max}, \forall_{t=1,\dots,T} \quad (14)$$

Equation (14) calculates the consumption of electricity at each time interval t by means of the product between the matrix $DSA_{t,i}$ and the vector with the power requirements of each apparatus p_i. Thus, Equation (13) indicates when the consumption of electric energy in a given time interval t exceeds the minimum and maximum limits determined by the variables d^{min}/d^{max}, respectively.

Constraint 2 (Equation 15) defines that the difference between the consumption of electric energy in the time interval t, obtained by the product of $DSA_{t,i}.p_i$ and the energy consumption in the subsequent time interval $t+1$, indicated by the product of $DSA_{t+1,i}.p_i$, considering the ramping down limitr r^D for the time interval t. Therefore, Equation (15) aims to limit the increase in electric energy consumption in the interval of time t caused by the displacement of loads from subsequent time interval $t+1$.

$$\sum_{i=1}^{N}(DSA_{t,i} - DSA_{t+1,i}) \,.\, p_i \leq r^D, \forall_{t=1,\dots,T-1} \tag{15}$$

Constraint 3 (Equation 16) defines that the difference between the energy consumption in the time interval $t+1$ obtained by the product of $DSA_{t+1,i}.p_i$ and the energy consumption in the previous time interval t, indicated by the product of $DSA_{t,i}.p_i$, does not exceed the ramping up limit r^U for the time interval t. Thus, Equation (16) aims to limit the increase of electric energy consumption in the interval of time $t+1$ caused by the displacement of the loads from previous time intervals t.

$$\sum_{i=1}^{N}(DSA_{t+1,i} - DSA_{t,i}) \,.\, p_i \leq r^U, \forall_{t=1,\dots,T-1} \tag{16}$$

Therefore, the constraints 2 (15) and 3 (16) help to stabilize the electric power system (EPS) in relation to any sharp displacements of loads over the time horizon T.

Constraint 4 (Equation 17) establishes the minimum daily consumption (*mdc*). The mdc is the product of the matrix $DSA_{t,1}$ and the vector of energy consumption e_i in residential appliances i when in operation, garanteeing a minimum daily usage of the residential appliances N.

$$\sum_{i=1}^{N}\sum_{t=1}^{T} DSA_{t,i} \,.\, e_i \geq mdc \tag{17}$$

The constraints 1–4 (Equations (14) to (17)) describe common features for the consumption of electricity. In this work, the home appliances are divided into three categories based on their operational characteristics (CHEN; WU; FU, 2012) as follows: interruptible and deferrable (A_I); uninterruptible and deferrable (A_{II}); and, uninterruptible and non-deferrable (A_{III}). Uninterruptible means that a task cannot be interrupted until it is completed. Non-deferrable and Deferrable determine whether the task must start at the first time slot of the operational window, or not. Based on these definitions, the restrictions that deal with the different categories of home appliances A_I, A_{II} and A_{III} can beare specified below.

Constraints for *f*$_2$ objective function:

Constraint 5 (18) states that the operational startup of category *A$_I$* home appliances may vary over the time horizon T provided that Req_i is respected. The Constraint 5 is active, it ensures the operation of the residential appliance i for a minimum time Req_i in a time horizon T. A violation of this rule implies failure to a a comply with the required operating time of the home appliance i, thus impairing the correct usage of the appliance.

$$\sum_{t=1}^{T} DSA_{t,i} \geq Req_i, \forall_i \in A_I \tag{18}$$

Constraint 6 (Equation 19) states that the operational startup of category A_{II} the home appliance can be delayed within the time horizon *T* but, once it has started, it cannot be interrupted. Therefore, the activation of this constraint ensures that the execution of the residential appliance i over of a time horizon T, has a minimum duration required for a number of consecutive time intervals greater than or equal to Req_i. A breach of this restriction infringes the uninterrupted performance of A_{II} appliances.

$$\sum_{q=1}^{T-Req_i} \prod_{t=q}^{Req_i+(q-1)} DSA_{t,i} \geq 1, \forall_i \in A_{II} \tag{19}$$

Constraint 7 (Equation 20) establishes that the operation of a category A_{III} home appliance between its startup (ST_i) and end (ET_i), as defined by the consumer, is uninterruptible for the required time Req_i in the time horizon T. When Constraint 7 is active it ensures tha, *t* the operation of the residential appliance i of category A_{III} takes place for the minimum time defined by Req_i between the opening times ST_i and end ET_i defined by the consumer. Violation of this restriction makes the uninterrupted and non-deferrable operation of these A_{III} residential appliances impossible.

$$\sum_{ST_i}^{ET_i} DSA_{t,i} \geq Req_i, \forall_i \in A_{III} \tag{20}$$

3.3 Final Considerations

In this chapter, the concepts involving the Home Energy Management System were presented, highlighting the HEMS architecture is emphasizing its main components: AMI, SM, EMC, and Home Appliances. The EMC functionality was detailed in Section 3.2 because it is the part implemented in this thesis.

A mathematically formulated multi-objective DR optimization model was presented as nonlinear programming (NLP) problem to determine the optimal scheduling of home appliances considering real-time pricing (RTP) as well as different categories of the appliance. The multi-objective DR optimization model aims to minimize the cost of energy consumption and minimally affect convenience (satisfaction/comfort) of end consumers. The main constraints are minimum and maximum load limits for each time period; ramp limits; minimum consumption within the planning horizon; and some restrictions for the different home appliance categories.

Chapter 4

ANALYSIS OF THE RESULTS

This chapter presents an analysis of the results through the HEMS using the different optimization techniques LINGO, GA, PSO and NSGA-II for the mono-objective and multi-objective DR optimization model, respectively.

4.1 Initial Considerations

The DR optimization model presented in this work was based on the load shifting technique that modifies the pattern of residential electricity consumption over the time horizon (*DENG et al.*, 2015). Thus, the demand usually required in peak periods was shifted to another time of lower consumption; consequently, the consumer maintained the same total daily consumption without overloading the system during peak periods.

Therefore, in the experiments of this thesis was considered the preferences of the consumers regarding their home appliances, the price of electric energy per hour and the diversity of geographic information based on the location, the climate and their respective implications for each region of Brazil, as illustrated in Figure 13.

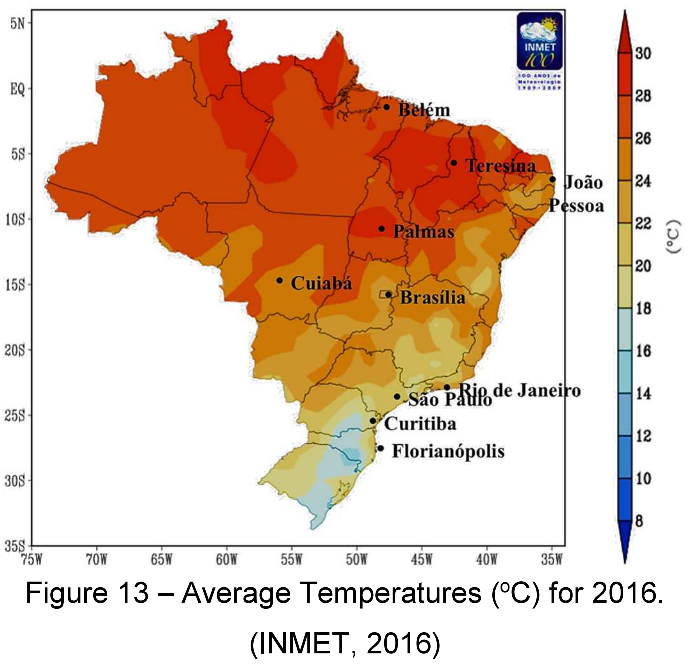

Figure 13 – Average Temperatures (ºC) for 2016.
(INMET, 2016)

Additionally, Figure 14 shows the average of the maximum and minimum temperature for the year 2016 (INMET, 2016). Due to the dimensionality of Brazil, there are several temperature values for each region throughout the year causing different profiles of family behaviour concerning daily routines.

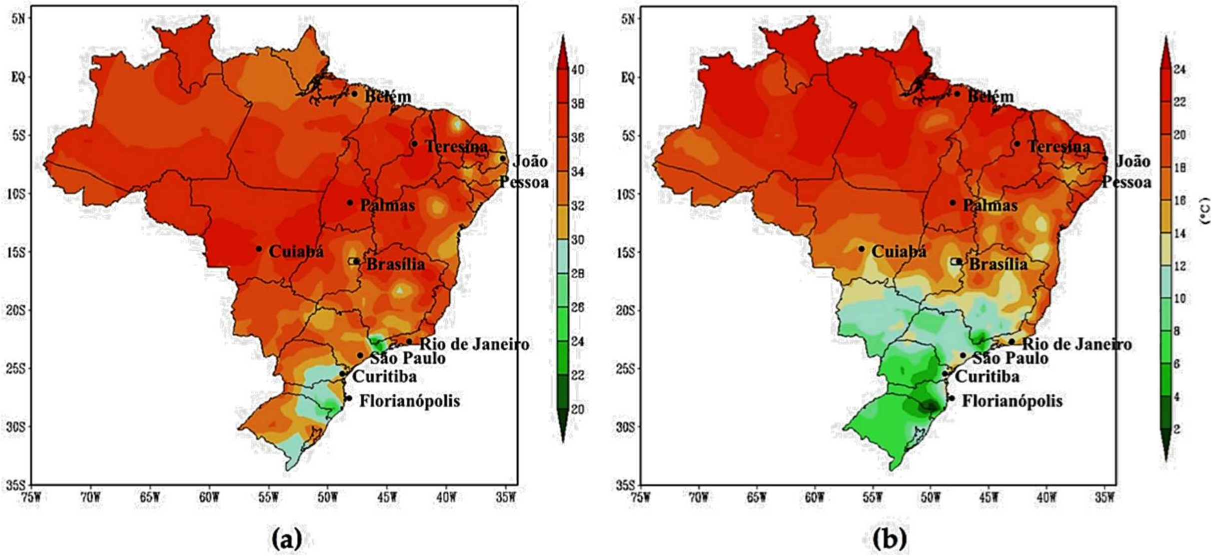

Figure 14 – Temperatures (ºC) for 2016 by Cities: (a) average annual maximum temperature; and (b) average annual minimum temperature.

(INMET, 2016)

In this chapter, an analysis of the results obtained through the HEMS using the different optimization techniques LINGO, GA, PSO and NSGA-II for the mono-objective and multi-objective DR optimization model, respectively were presented.

Under these circumstances, due to the complexity of optimizing combinatorial problems involving the minimization of the cost related to the electricity consumption with the minimum effects on the convenience levels of the end consumers, computational simulations are necessary to compare the results obtained through optimization techniques LINGO, GA, PSO, and NSGA-II. This comparison can demonstrate the efficiency of the different techniques in the optimization process for the various home appliance categories. Therefore, the problem formulated in this thesis is solved using LINGO, GA PSO and NSGA-II optimization techniques.

4.2 Experimental Scenario 1 (Mono-Objective)

In this section, Equation (13) of the DR optimization model, which was described in detail in Section 3.2, is no longer an objective function and becomes an equation for calculating the inconvenience value (dissatisfaction/discomfort) for end consumers. In addition, the analysis of the results through LINGO, GA and PSO techniques, the discussions and the parameters used in the optimization process related to load schedule are presented.

4.2.1 Optimization Process by LINGO

In the experiments, Equation (13) of the DR optimization model stops being an objective function and becomes an equation for calculating the consumer inconvenience value in order to evaluate how the operating schedule of the home appliances can interfere with the satisfaction and comfort of the end consumers through inconvenience values. Therefore, Equation (13) compares the real energy consumption (*baseline*) in the time interval t for the home appliance *i* of the family, which is analyzed through the Load Profile Generation (LPG) tool (PFLUGRADT, 2016), and the consumption obtained by the optimization techniques (DSA) used in the computational simulations.

The inconvenience value checks the difference between the actual consumption and the suggested consumption for each time interval and each device under consideration and shows how much the consumption suggested by the optimization technique distances itself from the actual consumption pattern of the family under analysis. Assuming that the solution that is considered optimal will affect the normal use of residential appliances minimally, besides reducing the final price, then the smaller the difference between the normal family consumption and the proposed optimized one, the better the solution will be. Based on this assumption, the calculation of the inconvenience associated with a home appliance operation scheduling allows the consumer to decide whether or not to join the DR program.

The mathematical formulation was implemented in the software LINGO version 17.0 (

Appendix A: Script LINGO Nonlinear Programming) using an educational license. In the modelling, the information collected through the LPG tool (PFLUGRADT, 2016) was used as the database, referring to the consumption of residential electricity for the day of greatest and least energy consumption in the year 2016. The input and output data were aided by Microsoft Excel.

In the experiments, some parameters were considered, as described in Table 2, for 30 families with different profiles of energy consumption (Profile 1 – a single adult, Profile 2 – two adults, and Profile 3 – two adults with three children).

Table 2 – Parameters.

Parameter	Value
Maximum demand for time interval (d^{max})	3 kW
Minimum demand for time interval (d^{min})	0 kW
Ramping up limit (r^U)	1 kWh
Ramping down limit (r^D)	1kWh

Other adjustments were also required to complete the optimization process by LINGO, such as Global Solver Options, NLP Solver Version, Derivatives (First Order) and Strategies using the following settings respectively: Use Global Solver, Version 3.0, Solver Decides and Quadratic Recognition and SLP Directions. Also, each city has a different mdc parameter as each family had a consumption based on the geographic locations with their respective climates and temperatures. Furthermore, the profile had different numbers of home appliances: Profile 1 (290 appliances), Profile 2 (330 appliances) and Profile 3 (230 appliances), totalling 850 appliances for analysis. Table 3 shows the load profiles and the different categories of the home appliances classified according to their respective categories (interruptible and deferrable (A_I), uninterruptible and deferrable (A_II) and uninterruptible and non-deferrable (A_III)). An "interruptible" task may be stopped/interrupted before it finishes while an "uninterruptible" task may not be stopped/interrupted before it finishes. The term "non-deferrable" means that the task must start at the first time slot of the operational window, while "deferrable" means that this is not obligatory (CHEN; WU; FU, 2012).

Table 3 – Profiles and Categories of Home Appliances.

Profile	Categories	Home Appliances
1	A_I	Light 100 W, 20 W, and 60 W, SAT-Receiver, TV, Cell Phone Charging, Playstation, Microsoft Xbox, Laptop, CD/DVD Player, Computer, Home Cinema System, DVB-T Receiver, Router, Computer Screen, Kitchen Radio.
	A_{II}	Wine Cellar, Steam Iron, Hair Dryer, Electric Razor, Electric Stove, Electronic Hometrainer, Microwave, Juicer, Washing Machine, Toaster, Electric Kettle, Nespresso Coffee Machine.
	A_{III}	Refrigerator, Air Conditioning, Electric Heater, Freezer, Dryer.
2	A_I	Light 100 W, 20 W, and 60 W, SAT-Receiver, TV, Playstation, Laptop, CD/DVD Player, Computer, DVB-T Receiver, Router, Computer Screen.
	A_{II}	Wine Cellar, Steam Iron, Food Multiprocessor, Microwave, Washing Machine, Electric Kettle, Nespresso Coffee Machine.
	A_{III}	Refrigerator, Air Conditioning, Electric Heater, Freezer.
3	A_I	Light 100 W, 20 W, and 60 W, SAT-Receiver, TV, Cell Phone Charging, Microsoft Xbox, Laptop, CD/DVD Player, Computer, DVB-T Receiver, Router, Computer Screen, Kitchen Radio.
	A_{II}	Wine Cellar, Steam Iron, Hair Dryer, Electric Stove, Microwave, Juicer, Washing Machine, Toaster, Electric Kettle, Nespresso Coffee Machine.
	A_{III}	Refrigerator, Air Conditioning, Electric Heater, Freezer, Dryer.

Profile 1 – a single adult

Table 4 and Figure 15 displays a comparison of the results for the total cost of electricity for families living in the 10 Brazilian capitals on the day of the highest energy consumption. Thus, the family living in the city of Rio de Janeiro - RJ, compared to the other families in other cities (Belém-PA, Palmas-TO, Brasília-DF, Cuiabá-MT, João Pessoa-PB, Teresina-PI, São Paulo-SP, Curitiba-PR, and Florianópolis-SC) had the largest reduction in cost of electricity from R$ 0.94 to R$ 0.84.

Table 4 – Cost of Electricity by Family on the Day of the Highest Energy Consumption (Profile 1).

Family	Cities	Cost without DR (R$)	Cost with DR (R$)	Reduction (%)
I	Belém-PA	2.26	2.14	5.31
II	Palmas-TO	1.20	1.15	4.17
III	Brasília-DF	1.73	1.64	5.20
IV	Cuiabá-MT	1.39	1.35	2.88
V	João Pessoa-PB	1.74	1.66	4.60
VI	Teresina-PI	1.13	1.07	5.31
VII	Rio de Janeiro-RJ	0.94	0.84	10.64
VIII	São Paulo-SP	2.44	2.36	3.28
IX	Curitiba-PR	2.43	2.28	6.17
X	Florianópolis-SC	2.55	2.54	0.39

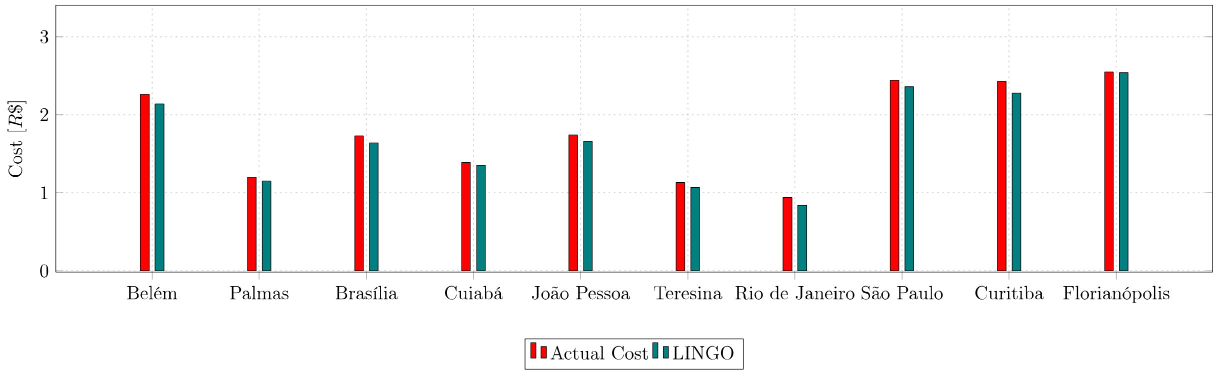

Figure 15 – Cost of Electricity by Family on the Day of the Highest Energy Consumption (Profile 1).

Another analysis was the evaluation of HEMS using the DR optimization model by LINGO to minimize the total cost of electricity on the day of the least consumption. Table 5 and Figure 16 show that it was possible to reduce the total cost of electricity in all the families studied. The family in João Pessoa-PB had the largest reduction in the cost of electricity (from R$ 0.61 to R$ 0.32) if compared to other families.

Table 5 – Cost of Electricity by Family on the Day of the Lowest Energy Consumption (Profile 1).

Family	**Cities**	**Cost without DR (R$)**	**Cost with DR (R$)**	**Reduction (%)**
I	Belém-PA	0.76	0.72	5.26
II	Palmas-TO	0.92	0.87	5.43
III	Brasília-DF	0.34	0.28	17.65
IV	Cuiabá-MT	0.40	0.33	17.55
V	João Pessoa-PB	0.61	0.32	47.54
VI	Teresina-PI	1.08	0.97	10.19
VII	Rio de Janeiro-RJ	0.35	0.31	11.43
VIII	São Paulo-SP	0.53	0.47	11.32
IX	Curitiba-PR	0.19	0.17	10.53
X	Florianópolis-SC	0.32	0.28	12.50

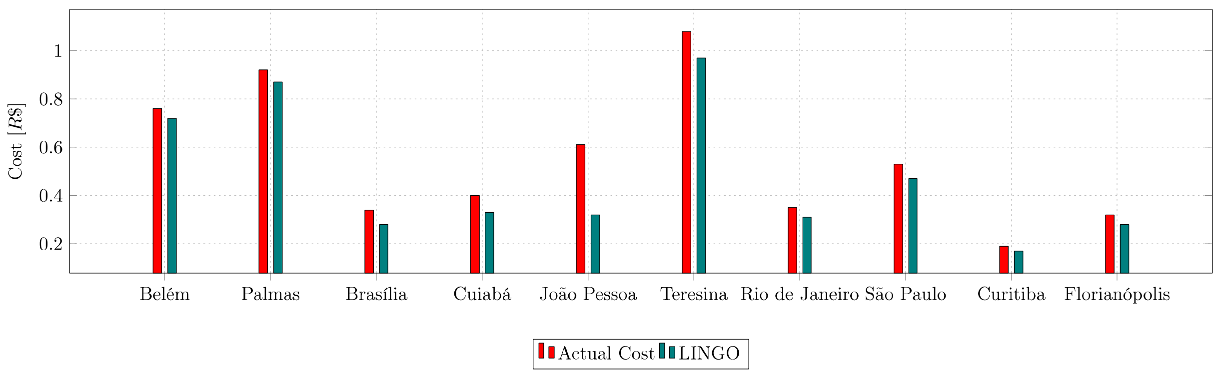

Figure 16 – Cost of Electricity by Family on the Day of the Lowest Energy Consumption (Profile 1).

Additionally, the inconvenience level for the days of highest and lowest energy consumption for each family was calculated. So, the highest inconvenience value found for the days of highest and lowest consumption of electric power was 144 and 102 for the families located in the cities of Curitiba-PR and João Pessoa-PB, respectively.

Table 6 and Table 7 summarizes the simulation results for the inconvenience in each family resident in Belém-PA, Palmas-TO, Brasília-DF, Cuiabá-MT, João Pessoa-PB, Teresina-PI, Rio de Janeiro-RJ, São Paulo-SP, Curitiba-PR, and Florianópolis-SC.

Table 6 – Inconvenience on the Day of the Highest Energy Consumption (Profile 1).

Family	Cities	Inconvenience
I	Belém-PA	118
II	Palmas-TO	112
III	Brasília-DF	92
IV	Cuiabá-MT	92
V	João Pessoa-PB	100
VI	Teresina-PI	122
VII	Rio de Janeiro-RJ	100
VIII	São Paulo-SP	106
IX	Curitiba-PR	144
X	Florianópolis-SC	78

Table 7 – Inconvenience on the Day of the Lowest Energy Consumption (Profile 1).

Family	Cities	Inconvenience
I	Belém-PA	89
II	Palmas-TO	87
III	Brasília-DF	77
IV	Cuiabá-MT	101
V	João Pessoa-PB	102
VI	Teresina-PI	93
VII	Rio de Janeiro-RJ	68
VIII	São Paulo-SP	80
IX	Curitiba-PR	54
X	Florianópolis-SC	70

Another analysis was the calculation of the *Trade-off* solution, that is, the ratio between each inconvenience unit caused to an end consumer and the reduction attributed to it, resulting in the total decrease (in R$) for each inconvenience unit. Figure 17 shows the simulation results of the *Trade-off* for the families living in Curitiba-PR and João Pessoa-PB, who were the ones that had the highest inconvenience value for the day of the highest and lowest consumption of electric power.

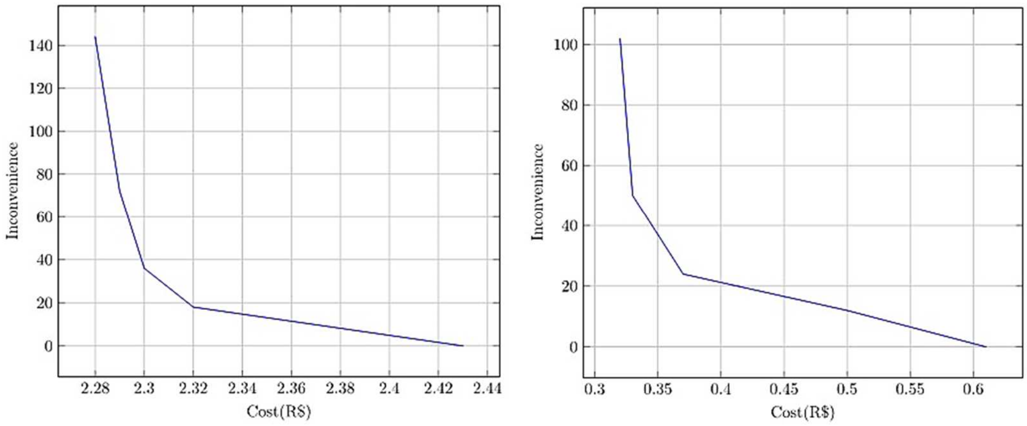

Figure 17 – a) *Trade-off* on Day of the Highest Energy Consumption; b) *Trade-off* on Day of the Lowest Energy Consumption (Profile 1).

Profile 2 – two adults

Table 8 and Figure 18 reflect the total electricity cost of each family for the day of highest energy consumption. The family resided in the city of João Pessoa-PB presented the largest reduction in cost associated with the electricity consumption compared to the other Brazilian families.

Table 8 – Cost of Electricity by Family on the Day of the Highest Energy Consumption (Profile 2).

Family	Cities	Cost without DR (R$)	Cost with DR (R$)	Reduction (%)
I	Belém-PA	2.17	2.03	6.45
II	Palmas-TO	4.29	3.75	12.59
III	Brasília-DF	4.18	3.60	13.88
IV	Cuiabá-MT	5.39	4.71	12.62
V	João Pessoa-PB	4.10	3.50	14.63
VI	Teresina-PI	5.02	4.87	2.99
VII	Rio de Janeiro-RJ	5.06	4.51	10.87
VIII	São Paulo-SP	4.04	3.77	6.68
IX	Curitiba-PR	5.44	4.99	8.27
X	Florianópolis-SC	4.79	4.15	13.36

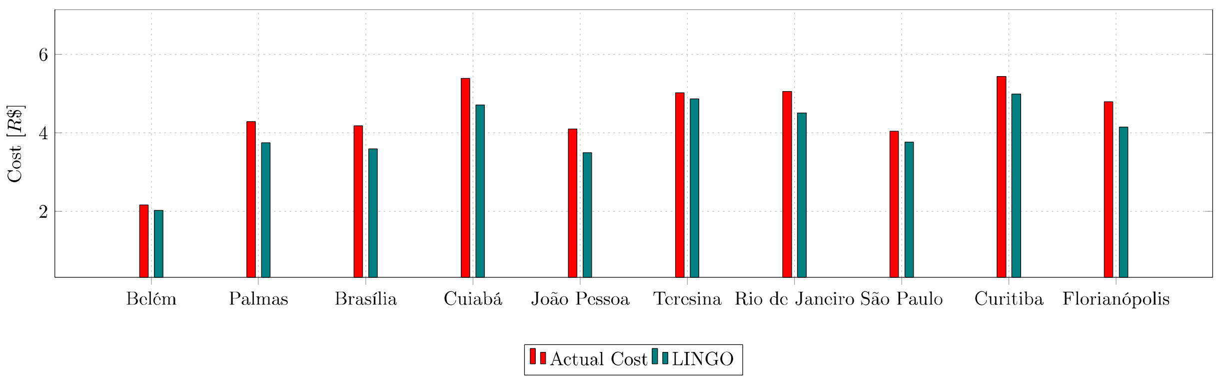

Figure 18 – Cost of Electricity by Family on the Day of the Highest Energy Consumption (Profile 2).

In addition, experiments were performed considering the day of the lowest energy consumption for Profile 2. Thus, the family living in the city of Belém-PA obtained the largest reduction in the total cost of electricity (from R$ 0.52 to R$ 0.41) compared to other families in the cities of Palmas-TO, Brasília-DF, Cuiabá-MT, João Pessoa-PB, Teresina-PI, Rio from January-RJ, São Paulo-SP, Curitiba-PR, and Florianópolis-SC. Moreover, it should be pointed out that the family residing in the city of Cuiabá-MT had the lowest reduction in the total cost of electricity due to the fact that the refrigerator, freezer and air conditioners have non-flexible loads and represent 98% of the energy consumption of the house. Table 9 and Figure 19 show the performance of each family by the optimization process using the DR optimization model for the day with the lowest energy consumption.

Table 9 – Cost of Electricity by Family on the Day of the Lowest Energy Consumption (Profile 1).

Family	Cities	Cost without DR (R$)	Cost with DR (R$)	Reduction (%)
I	Belém-PA	0.52	0.41	21.15
II	Palmas-TO	1.85	1.76	4.86
III	Brasília-DF	1.38	1.28	7.25
IV	Cuiabá-MT	0.8524	0.8522	0.02
V	João Pessoa-PB	1.06	1.00	5.66
VI	Teresina-PI	1.59	1.58	0.63
VII	Rio de Janeiro-RJ	0.74	0.69	6.76
VIII	São Paulo-SP	1.13	1.02	9.73
IX	Curitiba-PR	1.24	1.14	8.06
X	Florianópolis-SC	0.32	0.31	3.13

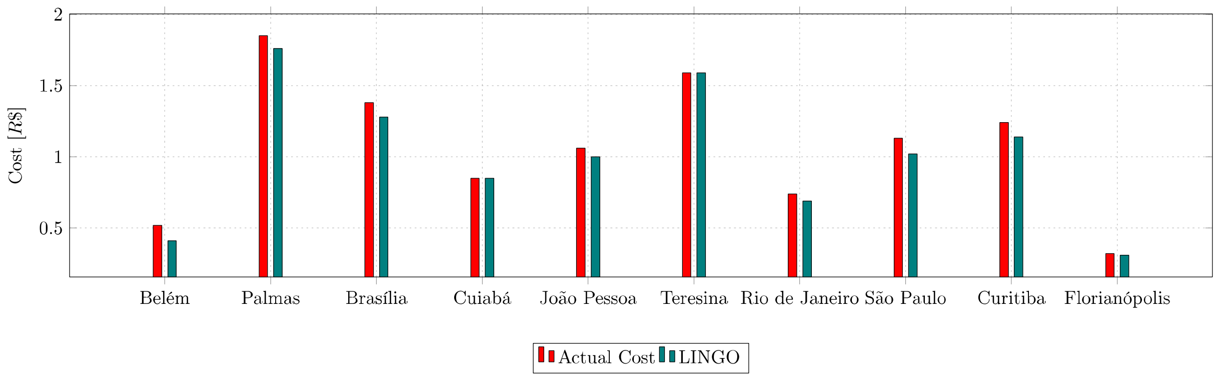

Figure 19 – Cost of Electricity by Family on the Day of the Lowest Energy Consumption (Profile 2).

Table 10 and Table 11 show the inconvenience level results for the end consumers on the days of highest and lowest electricity consumption. The inconvenience values show that the families living in Cuiabá-MT (inconvenience: 168) and Rio de Janeiro-RJ (inconvenience: 131) obtained the highest results for the inconvenience level.

Table 10 – Inconvenience on the Day of the Highest Energy Consumption (Profile 2).

Family	Cities	Inconvenience
I	Belém-PA	144
II	Palmas-TO	158
III	Brasília-DF	162
IV	Cuiabá-MT	168
V	João Pessoa-PB	158
VI	Teresina-PI	129
VII	Rio de Janeiro-RJ	152
VIII	São Paulo-SP	152
IX	Curitiba-PR	144
X	Florianópolis-SC	132

Table 11 – Inconvenience on the Day of the Lowest Energy Consumption (Profile 2).

Family	Cities	Inconvenience
I	Belém-PA	108
II	Palmas-TO	124
III	Brasília-DF	110
IV	Cuiabá-MT	81
V	João Pessoa-PB	105
VI	Teresina-PI	100
VII	Rio de Janeiro-RJ	131
VIII	São Paulo-SP	111
IX	Curitiba-PR	100
X	Florianópolis-SC	70

Furthermore, based on these results, the *Trade-off* relationship between the inconvenience and the minimization of the electricity cost (in R$) obtained in each inconvenience unit was evaluated. Figure 20 gives the simulation results for the *Trade-off* of families living in Cuiabá-MT and João Pessoa-PB that had the highest inconvenience value for the days of the highest and lowest electricity consumption.

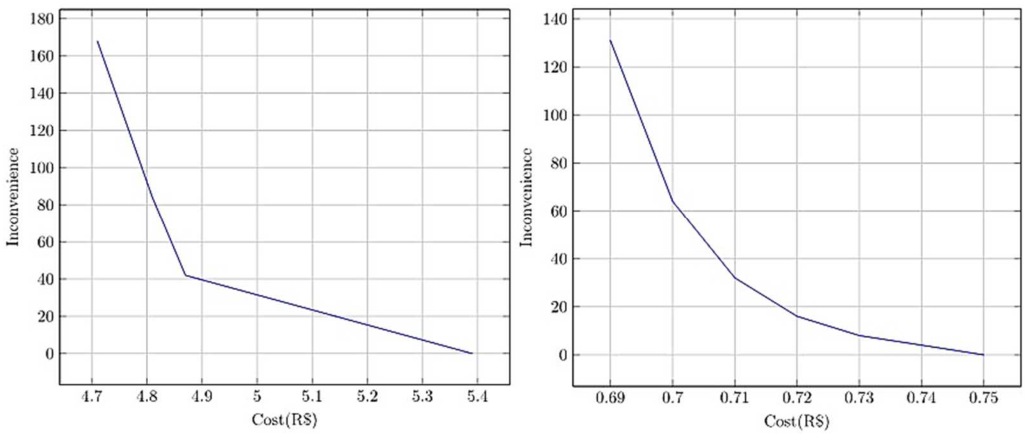

Figure 20 – a) *Trade-off* on Day of the Highest Energy Consumption; b) *Trade-off* on Day of the Lowest Energy Consumption (Profile 2).

Profile 3 – two adults with three children

The results show that the family living in Curitiba-PR had the highest values related to cost minimization associated with the consumption of electric energy compared to other families in the cities of Belém-PA, Palmas-TO, Brasília-DF, Cuiabá-MT, João Pessoa-PB, Teresina-PI, Rio de Janeiro-RJ, São Paulo-SP, Curitiba-PR, and Florianópolis-SC. Table 12 and Figure 21 summarize the results for Profile 3.

Table 12 – Cost of Electricity by Family on the Day of the Highest Energy Consumption (Profile 3).

Family	Cities	Cost without DR (R$)	Cost with DR (R$)	Reduction (%)
I	Belém-PA	8.40	8.00	4.76
II	Palmas-TO	8.02	7.50	6.48
III	Brasília-DF	1.64	1.54	6.10
IV	Cuiabá-MT	4.41	4.13	6.35
V	João Pessoa-PB	7.90	7.70	2.53
VI	Teresina-PI	7.55	7.31	3.18
VII	Rio de Janeiro-RJ	2.99	2.84	5.02
VIII	São Paulo-SP	8.10	8.08	0.25
IX	Curitiba-PR	7.92	7.33	7.45
X	Florianópolis-SC	8.41	8.32	1.07

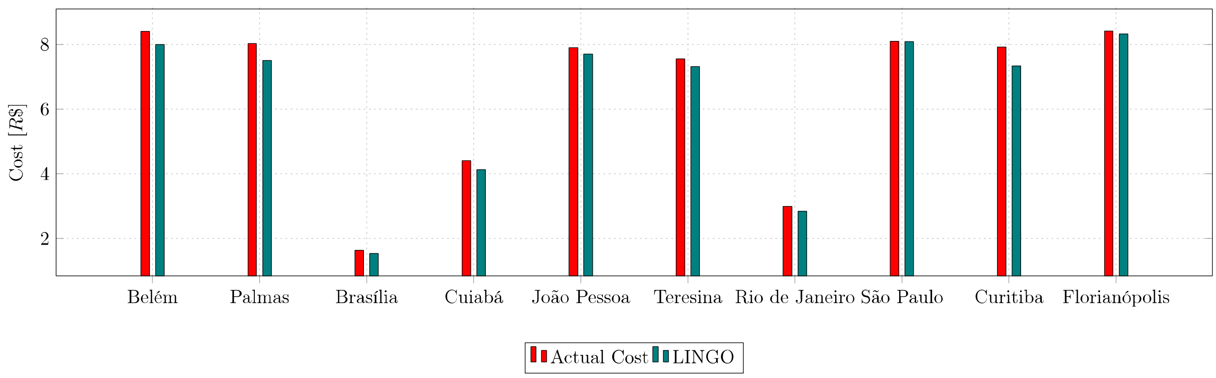

Figure 21 – Cost of Electricity by Family on the Day of the Highest Energy Consumption (Profile 3).

Table 13 and Figure 22 displays a comparison of the total cost of electricity for each family for the day with the least energy consumption. Thus, the family living in João Pessoa-PB had the greatest reduction in the cost related to the electricity consumption compared to other families in the cities of Belém-PA, Palmas-TO, Brasilia-DF, Cuiabá-MT, Teresina-PI, Rio de Janeiro-RJ, São Paulo-SP, Curitiba-PR, and Florianópolis-SC, decreasing from R$ 2.52 to R$ 1.48.

Table 13 – Cost of Electricity by Family on the Day of the Lowest Energy Consumption (Profile 3).

Family	Cities	Cost without DR (R$)	Cost with DR (R$)	Reduction (%)
I	Belém-PA	2.39	2.10	12.13
II	Palmas-TO	4.60	4.33	5.87
III	Brasília-DF	1.49	1.43	4.03
IV	Cuiabá-MT	1.84	1.53	16.85
V	João Pessoa-PB	2.52	1.48	41.27
VI	Teresina-PI	4.72	4.66	1.27
VII	Rio de Janeiro-RJ	1.90	1.82	4.21
VIII	São Paulo-SP	2.36	2.12	10.17
IX	Curitiba-PR	2.73	2.65	2.93
X	Florianópolis-SC	2.18	1.93	11.47

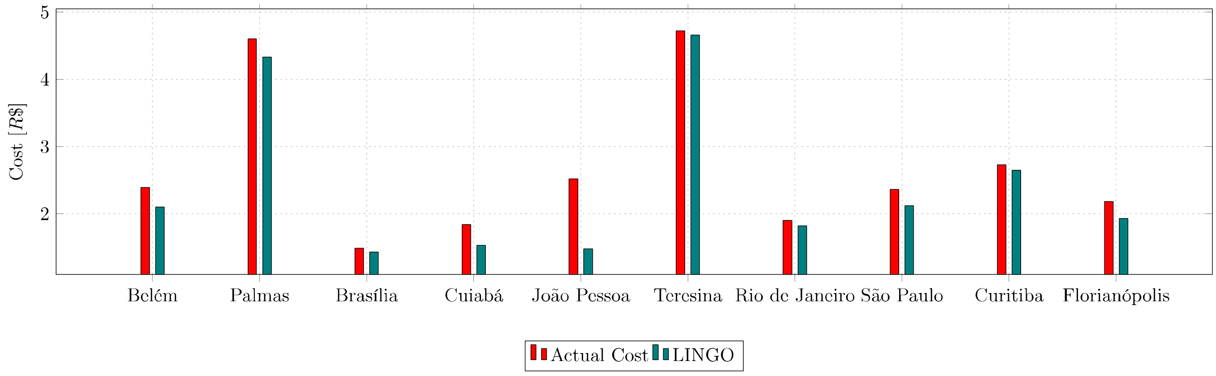

Figure 22 – Cost of Electricity by Family on the Day of the Lowest Energy Consumption (Profile 3).

In addition, Table 14 and Table 15 show the results for the inconvenience level for the end consumers about the use of their home appliances for the days of highest and lowest consumption of electric energy. Thus, families living in Belém-PA (inconvenience: 228) and João Pessoa-PB (inconvenience: 197) had the highest inconvenience rates.

Table 14 – Inconvenience on the Day of the Highest Energy Consumption (Profile 3).

Family	Cities	Inconvenience
I	Belém-PA	228
II	Palmas-TO	170
III	Brasília-DF	214
IV	Cuiabá -MT	190
V	João Pessoa-PB	180
VI	Teresina-PI	176
VII	Rio de Janeiro-RJ	210
VIII	São Paulo-SP	162
IX	Curitiba-PR	220
X	Florianópolis-SC	178

Table 15 – Inconvenience on the Day of the Lowest Energy Consumption (Profile 3).

Family	Cities	Inconvenience
I	Belém-PA	102
II	Palmas-TO	193
III	Brasília-DF	152
IV	Cuiabá-MT	170
V	João Pessoa-PB	197
VI	Teresina-PI	139
VII	Rio de Janeiro-RJ	165
VIII	São Paulo-SP	178
IX	Curitiba-PR	154
X	Florianópolis-SC	172

Another analysis was performed in order to verify, based on the results, the *Trade-off* relationship between the inconvenience and the total cost of electricity (in R$) for the days of highest and lowest energy consumption. Thus, Figure 23 shows the results obtained for *Trade-off* of families (residents in Belém-PA and João Pessoa-PB) who had the highest inconvenience values.

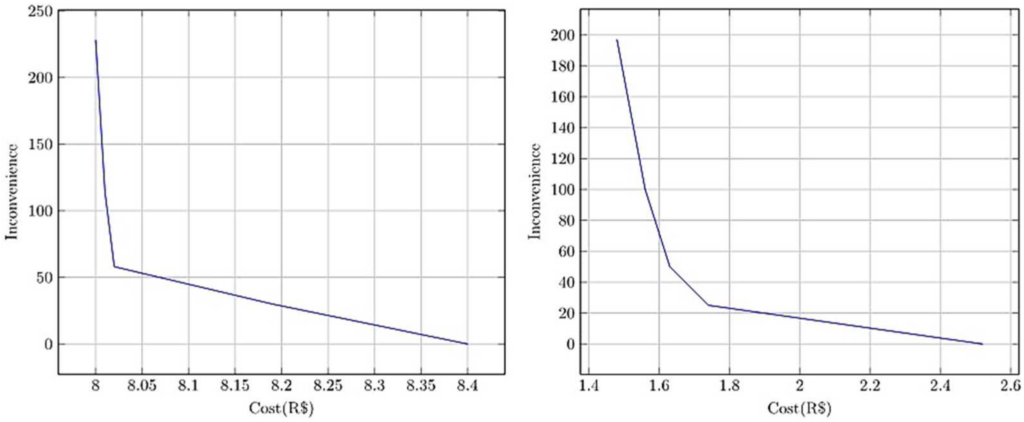

Figure 23 – a) *Trade-off* on Day of the Highest Energy Consumption; b) *Trade-off* on Day of the Lowest Energy Consumption (Profile 3)

4.2.2 Optimization Process by GA

The computational simulations were applied to 10 families, each with two working adults and two teenagers. The families were resident in 10 Brazilian cities (Belém-PA, Palmas-TO, Brasília-DF, Cuiabá-MT, João Pessoa-PB, Teresina-PI, Rio de Janeiro-RJ, São Paulo-SP, Curitiba-PR and Florianópolis-SC) located in the five different regions of the country, respectively: North, Central West, Northeast, Southeast and South.

These different regions present different climatic characteristics; for example, in the South and Southeast regions, there are certain times of the year when the temperatures are low, and at these times the residents do not use air conditioners with such frequency, while the North and Northeast regions have a subtropical climate that is divided into dry and rainy periods, with high temperatures throughout the year. Consequently, these residents use air conditioners much more frequently.

Thus, the families selected for the computational simulations have different patterns of electric energy consumption. In addition, each family was considered to have 29 appliances. Table 3 presents the residential appliances used in the computational simulations. For validation purposes, the optimization model DR uses the parameters in GA as shown in Table 16.

Table 16 – GA Parameters.

Parameter	Value
Population size	500
Maximum number of iterations	1.000
Selection method	Tournament (3)
Crossover method	One-Point
Crossover probability	85%
Mutation method	Binary
Mutation probability	1%

All these parameters used in the computational simulations involving the GA were obtained through a control mapping with the possible configuration values and, in this way, showed that this configuration could overcome the DR problem exemplified in this experiment scenario. Furthermore, Table 2 displays other parameters used by the GA technique in the computational simulations.

Simulation Results and Discussion for GA

The computational simulations included two versions of the DR proposed model: a full one and a relaxed version called Proposed Model (WT). The proposed model-WT used by the authors does not contemplate the particularities of operation of the different categories of residential appliances (interruptible and deferrable (A_I); uninterruptible and deferrable (A_{II}); and, uninterruptible and non-deferrable (A_{III})), as the full version of the proposed optimization model, presented in Section 3.2, does. However, both were used to analyze the impact of the operating characteristics of the different categories of residential appliances on reducing the cost of electricity as well as the level of satisfaction and comfort of the end consumers with the optimized programming for residential apparatuses. In addition, the optimization models proposed in (CONEJO; MORALES; BARINGO, 2010; LOGENTHIRAN; SRINIVASAN; SHUN, 2012) were also used for comparison.

The impact of DR, as well as the application of the proposed DR optimization model, was demonstrated through two aspects: the cost of electricity associated with consumption; and, the level of satisfaction and comfort of the final consumers. Table 17 and Figure 24 show a comparison of the cost of electricity of each family in each city, according to the LPG tool, as well as the values obtained through the GA optimization process using the formulations analyzed in this scenario. The results of the computational simulations show a reduction in the cost of electricity for each family with the inclusion of the DR program.

The models developed by the authors in (CONEJO; MORALES; BARINGO, 2010), (LOGENTHIRAN; SRINIVASAN; SHUN, 2012) and the Proposed Model (WT) obtained the largest reductions in the cost of electricity in the city of Rio de Janeiro-RJ from R$ 107.13 to R$ 62.07, R$ 73.54 and R$ 73.20, totaling a decrease of 42.06%, 31.35%, and 31.67%, respectively, in the final cost of electric energy. The DR optimization model proposed in this study obtained in the city of Rio de Janeiro-RJ a reduction in the cost of electricity from R$ 107.13 to R$ 99.44, which is a drop of 7.18% in the final cost of electricity.

However, in addition to the reduction of electricity consumption, this significant reduction of cost is only possible in the formulations developed by (CONEJO; MORALES; BARINGO, 2010), (LOGENTHIRAN; SRINIVASAN; SHUN, 2012) and the Proposed Model (WT) because they do not consider the particularities of the different categories of residential appliances, and therefore allow a greater reduction of the cost of electricity to be achieved. Thus, Figure 24 presents a synthesis of the electricity costs associated to the consumption of electric energy of each family according to the LPG tool for the models created in (CONEJO; MORALES; BARINGO, 2010) and (LOGENTHIRAN; SRINIVASAN; SHUN, 2012) and the model presented in this thesis.

Table 17 – Total Cost of Electric Energy.

Cities	Without DR (kWh)	With DR (kWh)				Reduction (%)			
		(CONEJO; MORALES; BARINGO, 2010)	(LOGENTHIRAN; RINIVASAN; SHUN, 2012)	Proposed Model	Proposed Model (WT)	(CONEJO; MORALES; BARINGO, 2010)	(LOGENTHIRA; RINIVASAN; SHUN, 2012)	Proposed Model	Proposed Model (WT)
Belém-PA	109.46	69.45	77.00	104.13	76.59	36.55%	29.65%	4.87%	30.03%
Palmas-TO	122.89	83.86	86.84	117.47	86.36	31.76%	29.34%	4.41%	29.73%
Brasília-DF	93.70	58.78	65.86	89.06	65.52	36.80%	29.18%	4.24%	29.55%
Cuiabá-MT	115.81	69.19	79.30	107.29	78.95	40.26%	31.53%	7.36%	31.83%
João Pessoa-PB	122.70	73.7	85.26	115.36	84.82	39.93%	30.51%	5.98%	30.87%
Teresina-PI	120.87	72.57	81.79	110.57	81.43	39.96%	32.33%	8.52%	32.63%
Rio de Janeiro-RJ	107.13	62.07	73.54	99.44	73.20	42.06%	31.35%	7.18%	31.67%
São Paulo-SP	87.87	52.76	61.06	82.56	60.71	39.96%	30.51%	6.04%	30.91%
Curitiba-PR	79.37	46.68	53.26	72.04	53.01	41.19%	32.90%	9.24%	33.21%
Florianópolis-SC	79.35	46.33	54.64	73.95	54.42	41.61%	31.14%	6.81%	31.42%

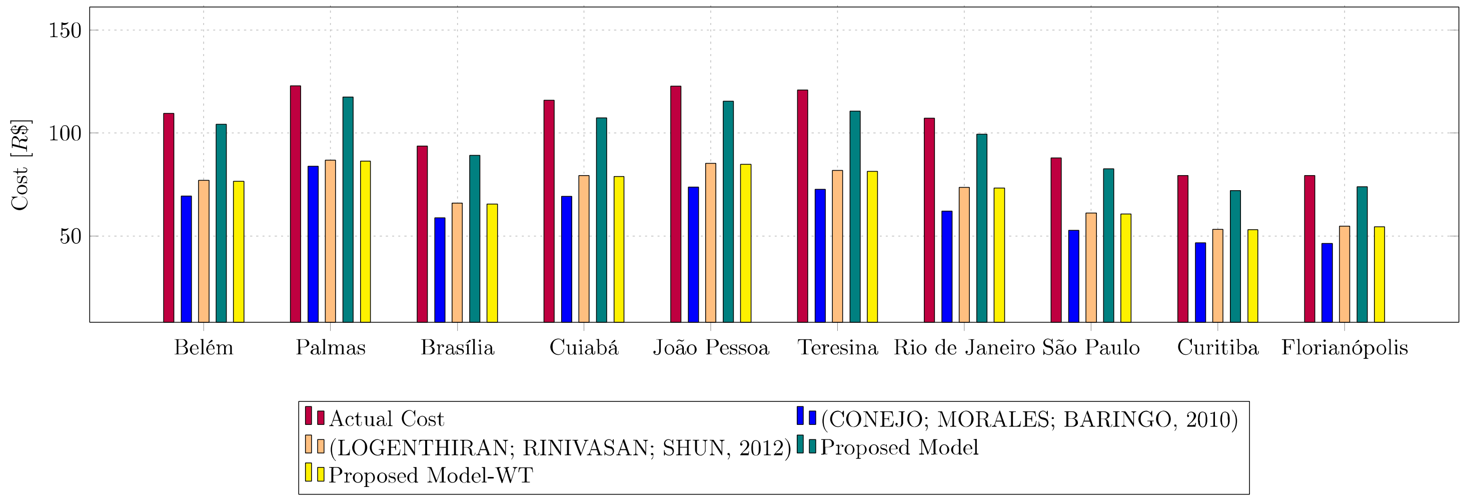

Figure 24 – Cost of Electricity by Family.
(VERAS *et al.*, 2018c).

Another analysis was the evaluation of the impact of the inconvenience, defined in Equation (13), which demonstrates how the change in the profile of using residential devices can interfere with the satisfaction and comfort of the final consumers. The results of the computational simulations show that, for example, in Brasília-DF, the model proposed in this study obtained a value of 62 for the level of inconvenience while the Proposed Model (WT) version and the formulation presented by the authors (LOGENTHIRAN; SRINIVASAN; SHUN, 2012) had values of 452 and 418, respectively. Table 18 gives a summary of all the values referring to the level of the inconvenience of each family.

Table 18 shows that the proposed DR optimization model had lower inconvenience values than the Proposed Model (WT) version and the model presented by the authors (LOGENTHIRAN; SRINIVASAN; SHUN, 2012). That is, the model in this study does not cause any significant level of dissatisfaction and discomfort to the final consumers in the face of changing the use of the devices over a time horizon.

Table 18 – Inconvenience by Family.

Family	**Cities**	**Inconvenience**		
		(LOGENTHIRAN; SRINIVASAN; SHUN, 2012)	**Proposed Model**	**Proposed Model (WT)**
I	Belém-PA	429	66	440
II	Palmas-TO	435	73	438
III	Brasília-DF	418	62	452
IV	Cuiabá-MT	422	70	440
V	João Pessoa-PB	418	78	440
VI	Teresina-PI	419	66	445
VII	Rio de Janeiro-RJ	414	70	456
VIII	São Paulo-SP	410	64	447
IX	Curitiba-PR	447	71	441
X	Florianópolis-SC	426	71	444

The formulations applied by (LOGENTHIRAN; SRINIVASAN; SHUN, 2012) and Proposed Model (WT), Figure 25, caused high levels of inconvenience as they did not differentiate the residential appliance categories in their formulation, while the model proposed in this paper considered the different particularities of the categories of home appliances, and consequently managed to reach the very low level of inconvenience. The inconvenience was not evaluated by the authors in (CONEJO; MORALES; BARINGO, 2010) because the structure of the formulation did not contemplate the load demand per device for each time interval, thus making such an analysis impossible.

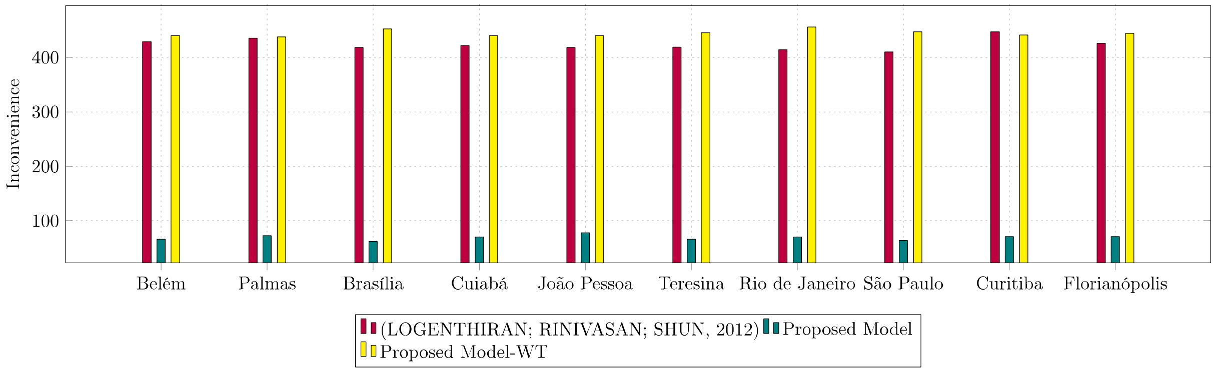

Figure 25 – Level of Inconvenience by Family.
(VERAS *et al.*, 2018c)

The results of the computational simulations show that the GA optimization process using the model proposed in this work managed to effectively manage the different categories of apparatuses in the ten residences. Thus, the proposed model is able to reduce the cost associated with the consumption of electric energy and the level of the inconvenience of the families when considering the preferences of the consumers in relation to the use of the residential apparatuses.

Moreover, new computational simulations were performed considering the day of highest and lowest electricity consumption in the year of 2016 for 30 families, with different electric energy consumption profiles (Profile 1 – a single adult; Profile 2 – two adults, and Profile 3 – two adults with three children). The families were resident in 10 Brazilian cities (Belém-PA, Palmas-TO, Brasília-DF, Cuiabá-MT, João Pessoa-PB, Teresina-PI, Rio de Janeiro-RJ, São Paulo-SP, Curitiba-PR and Florianópolis-SC) located in the five different regions of the country, respectively: North, Central West, Northeast, Southeast and South. The total time horizon in this study is given as $T = 24\ h$. Each time interval t means one hour and $t \in T$ such that: $T = \{1\ h, 2\ h \ldots 24\ h\}$, for each family between 1 January and 31 December 2016.

Each profile had different numbers of home appliances: Profile 1 (290 appliances), Profile 2 (330 appliances) and Profile 3 (230 appliances), totaling 850 appliances for analysis. Table 3 shows the load profiles and the different categories of the home appliances. In the computer simulations exemplified below, some parameters were considered for each family as presented in Table 2. Other parameters shown in Table 16 were used to develop GA using the DR optimization model contained in the EMC.

Profile 1 – a single adult

The results of the computational simulations indicate that the family living in Rio de Janeiro compared to other families reduced the total cost of electricity from R$ 0.94 to R$ 0.88, providing the best results related to cost minimization associated with energy consumption. Table 19 and Figure 26 summarize the results of the computational simulations the day of high electric energy consumption in profile 1.

Table 19 – Cost of Electricity by Family on the Day of the Highest Energy Consumption (Profile 1).

Family	Cities	Cost Without DR (R$)	Cost With DR (R$)	Reduction (%)
I	Belém-PA	2.26	2.19	3.10
II	Palmas-TO	1.20	1.18	1.67
III	Brasília-DF	1.73	1.65	4.62
IV	Cuiabá-MT	1.39	1.36	2.16
V	João Pessoa-PB	1.74	1.68	3.45
VI	Teresina-PI	1.13	1.11	1.77
VII	Rio de Janeiro-RJ	0.94	0.88	6.38
VII	São Paulo-SP	2.44	2.40	1.64
IX	Curitiba-PR	2.43	2.41	0.82
X	Florianópolis-SC	2.55	2.54	0.39

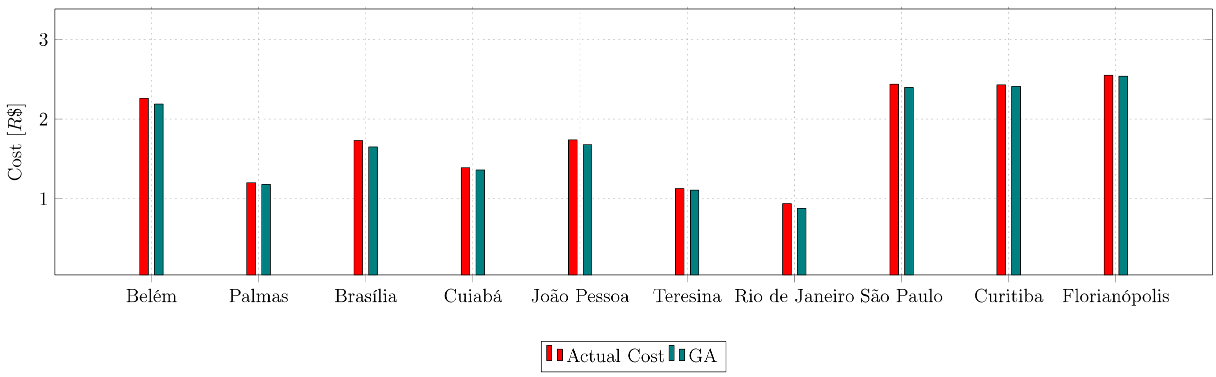

Figure 26 – Cost of Electricity by Family on the Day of the Highest Energy Consumption (Profile 1).

In the computational simulation results, for the day of less energy consumption, it is possible to observe that the family is living in the city of João Pessoa-PB, compared to the other families, obtained the largest reduction in the cost associated with the electricity consumption (from R$ 0.61 to R$ 0.43). Table 20 and Figure 27 summarize the total cost of electricity achieved by each household.

Table 20 – Cost of Electricity by Family on the Day of the Lowest Energy Consumption (Profile 1).

Family	Cities	Cost Without DR (R$)	Cost With DR (R$)	Reduction (%)
I	Belém-PA	0.76	0.75	1.32
II	Palmas-TO	0.92	0.89	3.26
III	Brasília-DF	0.34	0.32	5.88
IV	Cuiabá-MT	0.40	0.37	7.50
V	João Pessoa-PB	0.61	0.43	29.51
VI	Teresina-PI	1.08	1.05	2.78
VII	Rio de Janeiro-RJ	0.35	0.34	2.86
VII	São Paulo-SP	0.53	0.48	9.43
IX	Curitiba-PR	0.19	0.17	10.53
X	Florianópolis-SC	0.32	0.31	3.13

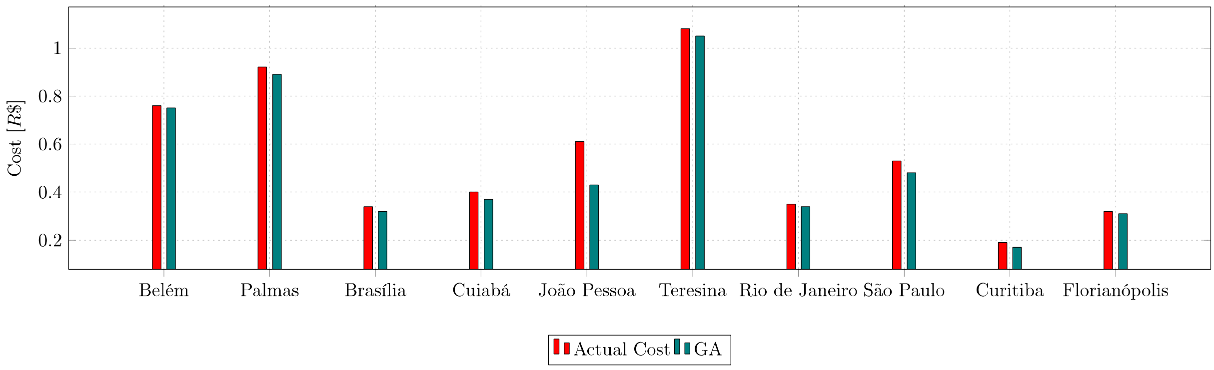

Figure 27 – Cost of Electricity by Family on the Day of the Lowest Energy Consumption (Profile 1)

In the inconvenience analysis, it is possible to realize that in the day of higher and lower energy consumption, the families living in the cities of Florianópolis-SC and Curitiba-PR obtained the lowest values about the inconvenience level, 80 and 54 respectively. In Table 21 and Table 22, the inconvenience values obtained in the computational simulations are exemplified for each family.

Table 21 – Inconvenience on the Day of the Highest Energy Consumption (Profile 1).

Family	Cities	Inconvenience
I	Belém-PA	121
II	Palmas-TO	115
III	Brasília-DF	93
IV	Cuiabá-MT	95
V	João Pessoa-PB	100

VI	Teresina-PI	123
VII	Rio de Janeiro-RJ	100
VIII	São Paulo-SP	107
IX	Curitiba-PR	144
X	Florianópolis-SC	80

Table 22 – Inconvenience on the Day of the Lowest Energy Consumption (Profile 1).

Family	Cities	Inconvenience
I	Belém-PA	90
II	Palmas-TO	89
III	Brasília-DF	79
IV	Cuiabá-MT	101
V	João Pessoa-PB	102
VI	Teresina-PI	96
VII	Rio de Janeiro-RJ	69
VIII	São Paulo-SP	81
IX	Curitiba-PR	54
X	Florianópolis-SC	73

Profile 2 – two adults

In this profile, it is clear that on the day of high energy consumption, the family living in Palmas-TO, in comparison with the other families, obtained the largest reduction in total electricity cost, from R$ 4.29 to R$ 3.93. Therefore, it reached the best computational results among the analyzed families. Table 23 and Figure 28 display the results of computational simulations for each family.

Table 23 – Cost of Electricity by Family on the Day of the Highest Energy Consumption (Profile 2).

Family	Cities	Cost Without DR (R$)	Cost With DR (R$)	Reduction (%)
I	Belém-PA	2.17	2.11	2.76
II	Palmas-TO	4.29	3.93	8.39
III	Brasília-DF	4.18	4.17	0.24
IV	Cuiabá-MT	5.39	5.04	6.49
V	João Pessoa-PB	4.10	3.97	3.17
VI	Teresina-PI	5.02	4.93	1.79
VII	Rio de Janeiro-RJ	5.06	5.05	0.20
VII	São Paulo-SP	4.04	3.84	4.95
IX	Curitiba-PR	5.44	5.04	7.35
X	Florianópolis-SC	4.79	4.43	7.52

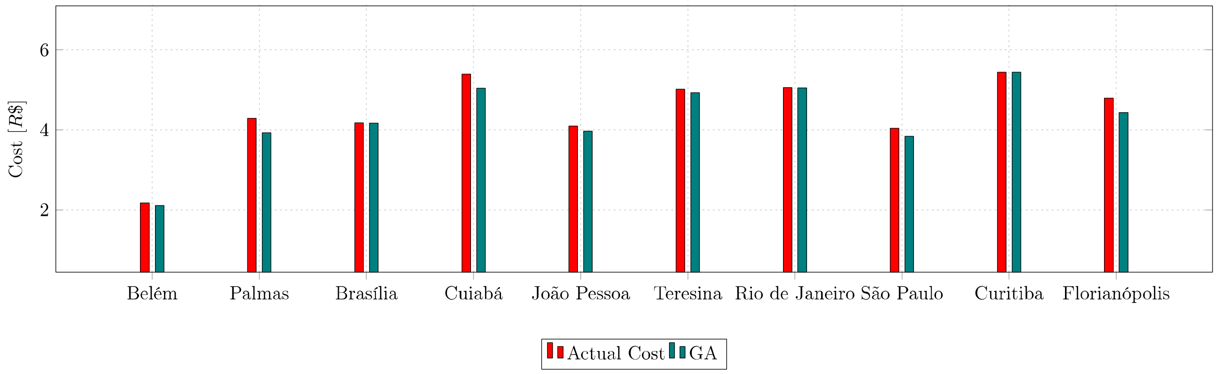

Figure 28 – Cost of Electricity by Family on the Day of the Highest Energy Consumption (Profile 2).

Table 24 and Figure 29 present the values related to the electricity cost reduction by each city in the day of less energy consumption. It is worth mentioning that the family living in São Paulo-SP obtained the best minimization of the annual cost in the electricity bill, from R$ 1.13 to R$ 1.02.

Table 24 – Cost of Electricity by Family on the Day of the Lowest Energy Consumption (Profile 2).

Family	**Cities**	**Cost Without DR (R$)**	**Cost With DR (R$)**	**Reduction (%)**
I	Belém-PA	0.75	0.52	1.32
II	Palmas-TO	1.85	1.77	4.32
III	Brasília-DF	1.38	1.33	3.62
IV	Cuiabá-MT	0.85	0.84	1.18
V	João Pessoa-PB	1.06	1.05	0.94
VI	Teresina-PI	1.59	1.55	2.52
VII	Rio de Janeiro-RJ	0.74	0.71	4.05
VII	São Paulo-SP	1.13	1.02	9.73
IX	Curitiba-PR	1.24	1.23	0.81
X	Florianópolis-SC	0.32	0.31	3.13

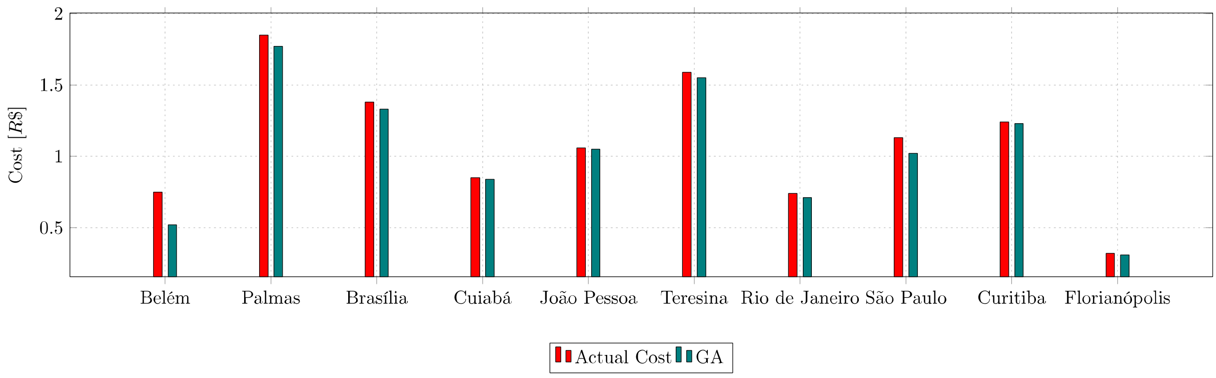

Figure 29 – Cost of Electricity by Family on the Day of the Lowest Energy Consumption (Profile 2).

Table 25 and Table 26 shows a comparison of the inconvenience level values reached through the GA optimization process in the EMC using the DR model presented in this work for each family/profile in each city. Thus, it is clear that the families living in the cities of Teresina-PI and Florianópolis-SC acquired the lowest values for the inconvenience level, being 129 and 73 for the day of higher and lower energy consumption, respectively.

Table 25 – Inconvenience on the Day of the Highest Energy Consumption (Profile 2).

Family	Cities	Inconvenience
I	Belém-PA	146
II	Palmas-TO	161
III	Brasília-DF	164
IV	Cuiabá-MT	170
V	João Pessoa-PB	161
VI	Teresina-PI	129
VII	Rio de Janeiro-RJ	152
VIII	São Paulo-SP	153
IX	Curitiba-PR	146
X	Florianópolis-SC	135

Table 26 – Inconvenience on the Day of the Lowest Energy Consumption (Profile 2).

Family	Cities	Inconvenience
I	Belém-PA	110
II	Palmas-TO	124
III	Brasília-DF	112
IV	Cuiabá-MT	83
V	João Pessoa-PB	107
VI	Teresina-PI	101
VII	Rio de Janeiro-RJ	134
VIII	São Paulo-SP	114
IX	Curitiba-PR	100
X	Florianópolis-SC	73

Profile 3 – two adults with three children

The simulations result for the day of high consumption show that the family living in the city of Rio de Janeiro-RJ, compared to other families in the cities of Belém-PA, Palmas-TO, Brasília-DF, Cuiabá-MT, João Pessoa-PB, Teresina-PI, São Paulo-SP, Curitiba-PR, and Florianópolis-SC, reduced the total cost of electricity from R$ 2.99 to R$ 2.84. Therefore, the family from Rio de Janeiro-RJ reached the highest values related to cost minimization associated with the electric energy consumption. Table 27 and Figure 30 summarize the results achieved in computational simulations.

Table 27 – Cost of Electricity by Family on the Day of the Highest Energy Consumption (Profile 3).

Family	Cities	Cost Without DR (R$)	Cost With DR (R$)	Reduction (%)
I	Belém-PA	8.40	8.38	0.24
II	Palmas-TO	8.02	7.94	1.00
III	Brasília-DF	1.64	1.58	3.66
IV	Cuiabá-MT	4.41	4.29	2.72
V	João Pessoa-PB	7.90	7.84	0.76
VI	Teresina-PI	7.55	7.48	0.93
VII	Rio de Janeiro-RJ	2.99	2.84	5.02
VII	São Paulo-SP	8.10	8.09	0.12
IX	Curitiba-PR	7.92	7.36	7.07
X	Florianópolis-SC	8.41	8.39	0.24

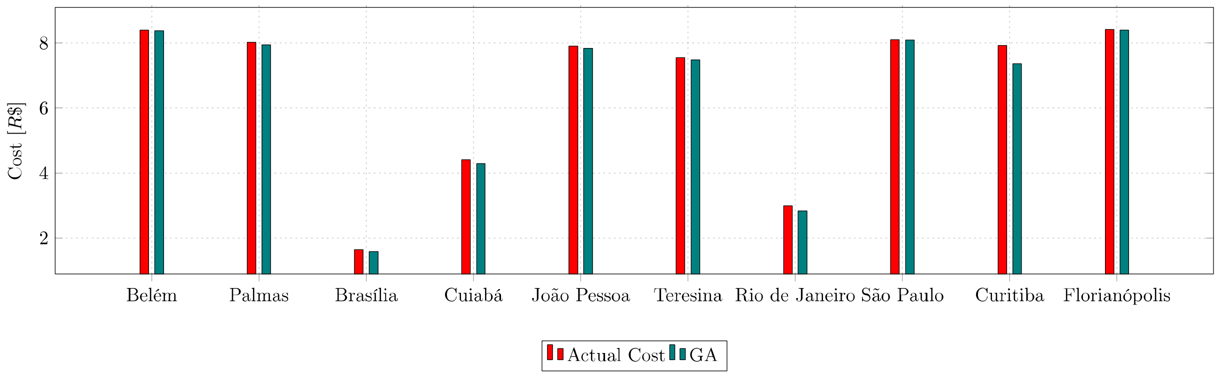

Figure 30 – Cost of Electricity by Family on the Day of the Highest Energy Consumption (Profile 3).

Table 28 and Figure 31 show a summary of the total cost of electricity per family in the day of less electric energy consumption. Thus, the family living in Florianópolis-SC obtained the highest minimization of the cost related to the electricity consumption, from R$ 2.18 to R$ 1.99.

Table 28 – Cost of Electricity by Family on the Day of the Lowest Energy Consumption (Profile 3).

Family	Cities	Cost Without DR (R$)	Cost With DR (R$)	Reduction (%)
I	Belém-PA	2.39	2.37	0.84
II	Palmas-TO	4.60	4.34	5.65
III	Brasília-DF	1.49	1.46	2.01
IV	Cuiabá-MT	1.84	1.77	3.80
V	João Pessoa-PB	2.52	2.35	6.75
VI	Teresina-PI	4.72	4.66	1.27

VII	Rio de Janeiro-RJ	1.90	1.89	0.53
VII	São Paulo-SP	2.36	2.33	1.27
IX	Curitiba-PR	2.73	2.71	0.73
X	Florianópolis-SC	2.18	1.99	8.72

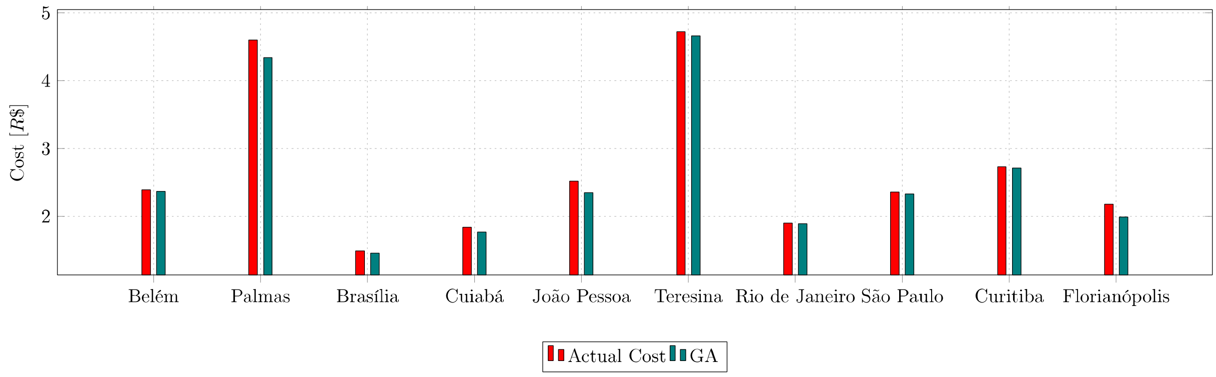

Figure 31 – Cost of Electricity by Family on the Day of the Lowest Energy Consumption (Profile 3).

In the inconvenience analysis of the days of higher and lower electric energy consumption, families living in São Paulo-SP and Belém-PA acquired the highest values for the inconvenience level, a total of 163 and 104, respectively. Table 29 and Table 30 summarizes the results achieved in computational simulations for the inconvenience level on days of higher and lower energy consumption.

Table 29 – Inconvenience on the Day of the Highest Energy Consumption (Profile 3).

Family	**Cities**	**Inconvenience**
I	Belém-PA	228
II	Palmas-TO	170
III	Brasília-DF	214
IV	Cuiabá-MT	191
V	João Pessoa-PB	181
VI	Teresina-PI	179
VII	Rio de Janeiro-RJ	213
VIII	São Paulo-SP	163
IX	Curitiba-PR	221
X	Florianópolis-SC	180

Table 30 – Inconvenience on the Day of the Lowest Energy Consumption (Profile 3).

Family	**Cities**	**Inconvenience**
I	Belém-PA	104
II	Palmas-TO	194
III	Brasília-DF	153
IV	Cuiabá-MT	170
V	João Pessoa-PB	197
VI	Teresina-PI	139
VII	Rio de Janeiro-RJ	165
VIII	São Paulo-SP	179
IX	Curitiba-PR	155
X	Florianópolis-SC	175

4.2.3 Optimization Process by PSO

The model presented in Section 3.2 was solved computationally by the PSO optimization technique. The computational simulations consider the day of highest and lowest electric energy consumption between January 1st and December 31st, 2016, for thirty families with different profiles of electric energy consumption (Profile 1 – a single adult; Profile 2 – two adults; and Profile 3 – two adults with three children). The families live in 10 Brazilian cities (Belém-PA, Palmas-TO, Brasília-DF, Cuiabá-MT, João Pessoa-PB, Teresina-PI, Rio de Janeiro-RJ, São Paulo-SP, Curitiba-PR and Florianópolis-SC) located in the five different regions of the country, respectively: North, Central West, Northeast, Southeast and South.

Also, each profile had different numbers of home appliances: Profile 1 (290 appliances), Profile 2 (330 appliances) and Profile 3 (230 appliances), totalling 850 appliances for analysis. Table 3 shows the load profiles and the different categories of home appliances. Furthermore, the total time horizon in this study is given as T=24h. Each time interval t means one hour and $t \in T$ such that: T={1h,2h…24h}. In the experiments, some parameters of the optimization process that schedules the loads in the residential scope (shown in Table 2) were considered for each family. Also, to solve the DR optimization model contained in the EMC through the PSO computationally, some adjustments must be made, using new parameters for the optimization technique as described in Table 31.

Table 31 – PSO Parameters.

Parameter	Value
Population Size	100
Maximum Number of Iterations	500
Particle Weight (Maximum)	0.9
Particle Weight (Minimum)	0.4
Acceleration Factors (c1)	2
Acceleration Factors (c2)	2
Initial Velocity	10% of position

Under these circumstances, an analysis of the results is shown in the experiments for different electricity consumption profiles, as follows.

Profile 1 – a single adult

Table 32 and Figure 32 present the results for the computational simulations of the minimization of the cost associated with the electric energy consumption by each family. The family living in São Paulo-SP had the greatest total cost reduction of electricity after the optimization process through PSO using the DR optimization model, from R$ 2.44 to R$ 2.40.

Table 32 – Cost of Electricity by Family on the Day of the Highest Energy Consumption (Profile 1).

Family	Cities	Cost without DR (R$)	Cost with DR (R$)	Reduction (%)
I	Belém-PA	2.26	2.20	2.65
II	Palmas-TO	1.20	1.18	3.69
III	Brasília-DF	1.73	1.69	2.86
IV	Cuiabá-MT	1.39	1.37	1.67
V	João Pessoa-PB	1.74	1.71	4.43
VI	Teresina-PI	1.13	1.09	0.25
VII	Rio de Janeiro-RJ	0.94	0.88	2.31
VII	São Paulo-SP	2.44	2.40	10.53
IX	Curitiba-PR	2.43	2.35	1.83
X	Florianópolis-SC	2.55	2.55	0.00

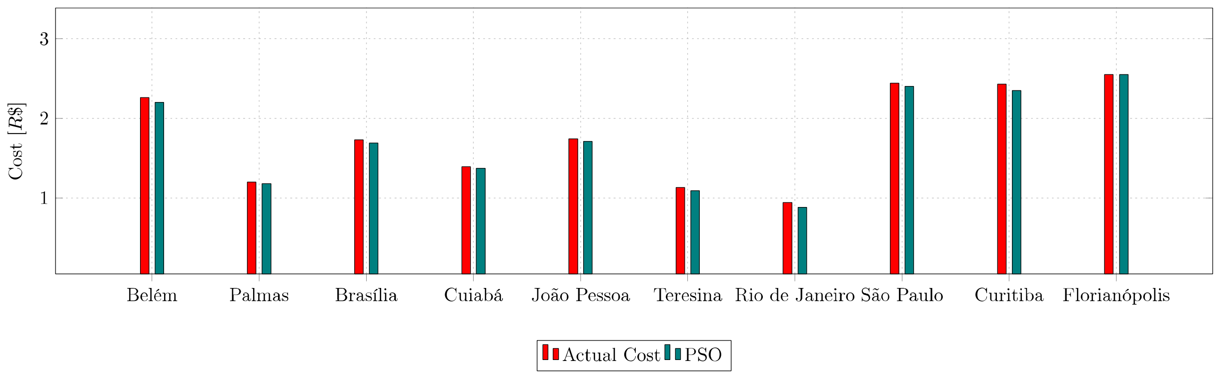

Figure 32 – Cost of Electricity by Family on the Day of the Highest Energy Consumption (Profile 1).

Table 33 and Figure 33 summarize all the values by each family related to the cost minimization associated with the electricity consumption obtained in the computational simulations through PSO using the DR optimization model presented in Chapter 3. This clearly shows a total cost reduction of electricity for all the families and the family, which lives in Brasília-DF, had the greatest reduction (from R$ 0.34 to R$ 0.28).

Table 33 – Cost of Electricity by Family on the Day of the Lowest Energy Consumption (Profile 1).

Family	Cities	Cost Without DR (R$)	Cost With DR (R$)	Reduction (%)
I	Belém-PA	0.76	0.74	2.63
II	Palmas-TO	0.92	0.89	3.26
III	Brasília-DF	0.34	0.28	17.65
IV	Cuiabá-MT	0.40	0.34	15.00
V	João Pessoa-PB	0.61	0.56	8.20
VI	Teresina-PI	1.08	1.01	6.48
VII	Rio de Janeiro-RJ	0.35	0.31	11.43
VII	São Paulo-SP	0.53	0.52	1.89
IX	Curitiba-PR	0.19	0.18	5.26
X	Florianópolis-SC	0.32	0.30	6.25

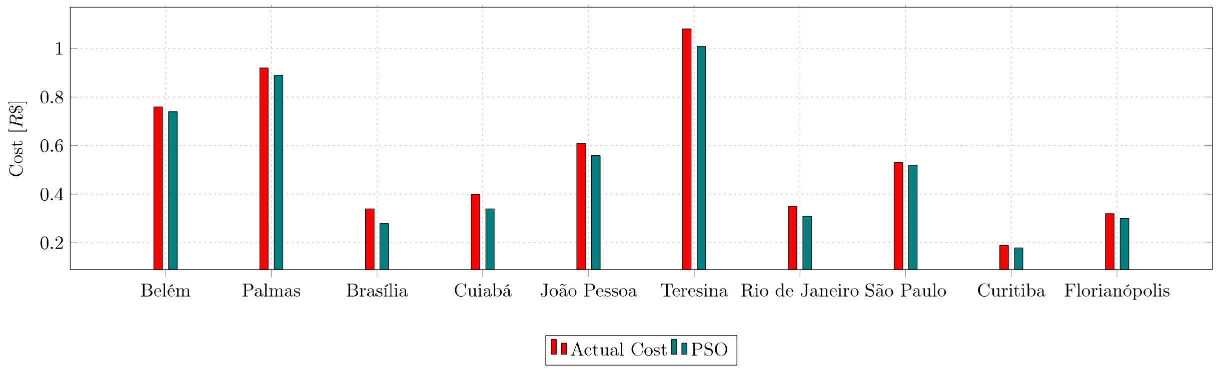

Figure 33 – Cost of Electricity by Family on the Day of the Lowest Energy Consumption (Profile 1).

Additionally, the inconvenience level for the day of the highest and lowest energy consumption for each family was calculated. The greatest inconvenience value found for the day of the highest and lowest electric energy consumption was 154 and 108 for the families located in the cities of Curitiba-PR and João Pessoa-PB, respectively.

Table 34 and Table 35 present a summary of the inconvenience simulation results for each family living in Belém-PA, Palmas-TO, Brasília-DF, Cuiabá-MT, João Pessoa-PB, Teresina-PI, Rio de Janeiro- RJ, São Paulo-SP, Curitiba-PR, and Florianópolis-SC.

Table 34 – Inconvenience on the Day of the Highest Energy Consumption (Profile 1).

Family	Cities	Inconvenience
I	Belém-PA	127
II	Palmas-TO	120
III	Brasília-DF	98

IV	Cuiabá-MT	103
V	João Pessoa-PB	110
VI	Teresina-PI	132
VII	Rio de Janeiro-RJ	107
VIII	São Paulo-SP	112
IX	Curitiba-PR	154
X	Florianópolis-SC	84

Table 35 – Inconvenience on the Day of the Lowest Energy Consumption (Profile 1).

Family	Cities	Inconvenience
I	Belém-PA	98
II	Palmas-TO	92
III	Brasília-DF	85
IV	Cuiabá-MT	107
V	João Pessoa-PB	108
VI	Teresina-PI	97
VII	Rio de Janeiro-RJ	77
VIII	São Paulo-SP	85
IX	Curitiba-PR	65
X	Florianópolis-SC	75

Profile 2 – two adults

Table 36 and Figure 34 display the results for the total electricity cost of each family for the day with the highest electricity consumption. The family living in Brasília-DF presented the highest values related to the minimization of costs associated with energy consumption in comparison to the other families in Belém-PA, Palmas-TO, Cuiabá-MT, João Pessoa-PB, Teresina-PI, Rio de Janeiro-RJ, São Paulo-SP, Curitiba-PR, and Florianópolis-SC, decreasing from R$ 4.18 to R$ 3.74.

Table 36 – Cost of Electricity by Family on the Day of the Highest Energy Consumption (Profile 2).

Family	Cities	Cost Without DR (R$)	Cost With DR (R$)	Reduction (%)
I	Belém-PA	2.17	2.09	3.69
II	Palmas-TO	4.29	4.10	4.43
III	Brasília-DF	4.18	3.74	10.53
IV	Cuiabá-MT	5.39	5.15	4.45
V	João Pessoa-PB	4.10	3.92	4.39
VI	Teresina-PI	5.02	4.92	1.99
VII	Rio de Janeiro-RJ	5.06	4.84	4.35
VII	São Paulo-SP	4.04	3.86	4.46
IX	Curitiba-PR	5.44	5.02	7.72
X	Florianópolis-SC	4.79	4.37	8.77

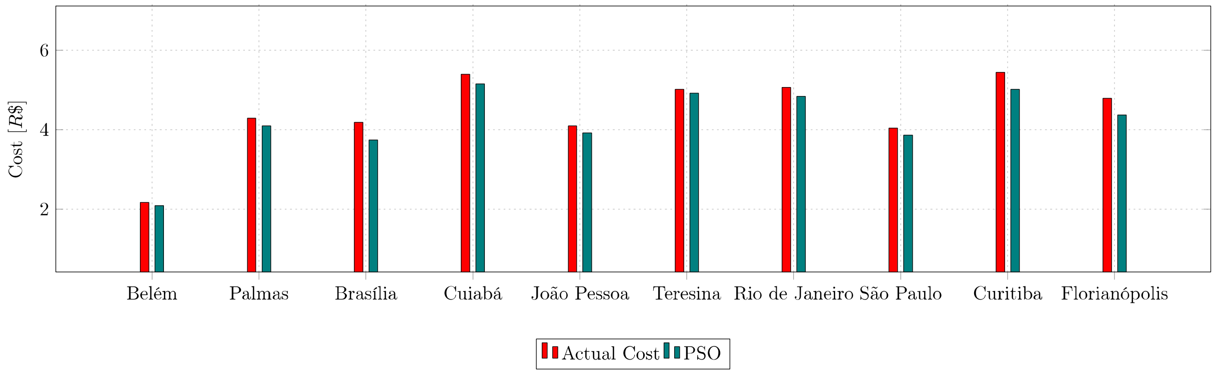

Figure 34 – Cost of Electricity by Family on the Day of the Highest Energy Consumption (Profile 2).

In the computational simulations involving the day of the lowest energy consumption, the family living in Rio de Janeiro-RJ had the largest reduction in the total cost of electricity compared to the other families in the cities of Belém-PA, Palmas-TO, Brasília- DF, Cuiabá-MT, João Pessoa-PB, Teresina-PI, São Paulo-SP, Curitiba-PR and Florianópolis-SC, decreasing from R$ 0.74 to R$ 0.69. Table 37 and Figure 35 show the performance of the optimization process using the PSO for each family.

Table 37 – Cost of Electricity by Family on the Day of the Lowest Energy Consumption (Profile 2).

Family	Cities	Cost Without DR (R$)	Cost With DR (R$)	Reduction (%)
I	Belém-PA	0.52	0.52	0.00
II	Palmas-TO	1.85	1.82	1.62
III	Brasília-DF	1.38	1.37	0.72
IV	Cuiabá-MT	0.85	0.84	1.18
V	João Pessoa-PB	1.06	1.04	1.89
VI	Teresina-PI	1.59	1.59	0.00
VII	Rio de Janeiro-RJ	0.74	0.69	6.76
VII	São Paulo-SP	1.13	1.07	5.31
IX	Curitiba-PR	1.24	1.22	1.61
X	Florianópolis-SC	0.32	0.31	3.13

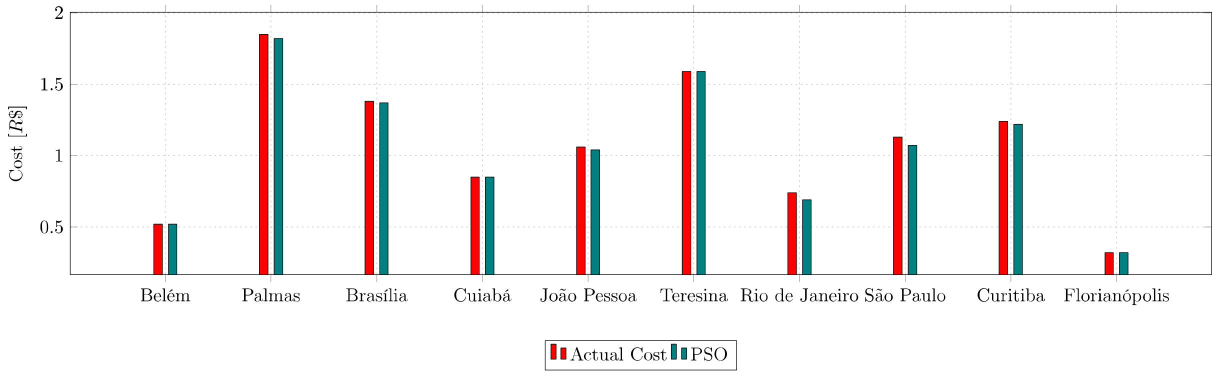

Figure 35 – Cost of Electricity by Family on the Day of the Lowest Energy Consumption (Profile 2).

Table 38 and Table 39 displays the results for the inconvenience level of the end consumers on the days of the highest and lowest electricity consumption. The inconvenience values show that the families living in Cuiabá-MT (inconvenience: 174) and Rio de Janeiro-RJ (inconvenience: 140) obtained the best results for the inconvenience level.

Table 38 – Inconvenience on the Day of the Highest Energy Consumption (Profile 2).

Family	Cities	Inconvenience
I	Belém-PA	153
II	Palmas-TO	162
III	Brasília-DF	167
IV	Cuiabá-MT	174
V	João Pessoa-PB	165
VI	Teresina-PI	138
VII	Rio de Janeiro-RJ	157
VIII	São Paulo-SP	156
IX	Curitiba-PR	156
X	Florianópolis-SC	139

Table 39 – Inconvenience on the Day of the Lowest Energy Consumption (Profile 2).

Family	Cities	Inconvenience
I	Belém-PA	120
II	Palmas-TO	130
III	Brasília-DF	114
IV	Cuiabá-MT	90
V	João Pessoa-PB	115
VI	Teresina-PI	109
VII	Rio de Janeiro-RJ	140
VIII	São Paulo-SP	123
IX	Curitiba-PR	105
X	Florianópolis-SC	76

Profile 3 – two adults with three children

The results show that the family living in Curitiba-PR had the highest cost minimization associated with the consumption of electric energy compared to the other families in the cities of Belém-PA, Palmas-TO, Brasília-DF, Cuiabá-MT, João Pessoa-PB, Teresina-PI, Rio de Janeiro-RJ, São Paulo-SP, Curitiba-PR and Florianópolis-SC. Table 40 and Figure 36 show a summary of the results for Profile 3. These results show that the EMC applying the PSO technique using the DR optimization model can reduce the cost associated with the electric energy consumption for all the families.

Table 40 – Cost of Electricity by Family on the Day of the Highest Energy Consumption (Profile 3).

Family	Cities	Cost Without DR (R$)	Cost with DR (R$)	Reduction (%)
I	Belém-PA	8.40	8.16	2.86
II	Palmas-TO	8.02	8.00	0.25
III	Brasília-DF	1.64	1.61	1.83
IV	Cuiabá-MT	4.41	4.29	2.72
V	João Pessoa-PB	7.90	7.89	0.13
VI	Teresina-PI	7.55	7.52	0.40
VII	Rio de Janeiro-RJ	2.99	2.90	3.01
VII	São Paulo-SP	8.10	8.09	0.12
IX	Curitiba-PR	7.92	7.62	3.79
X	Florianópolis-SC	8.41	8.32	1.07

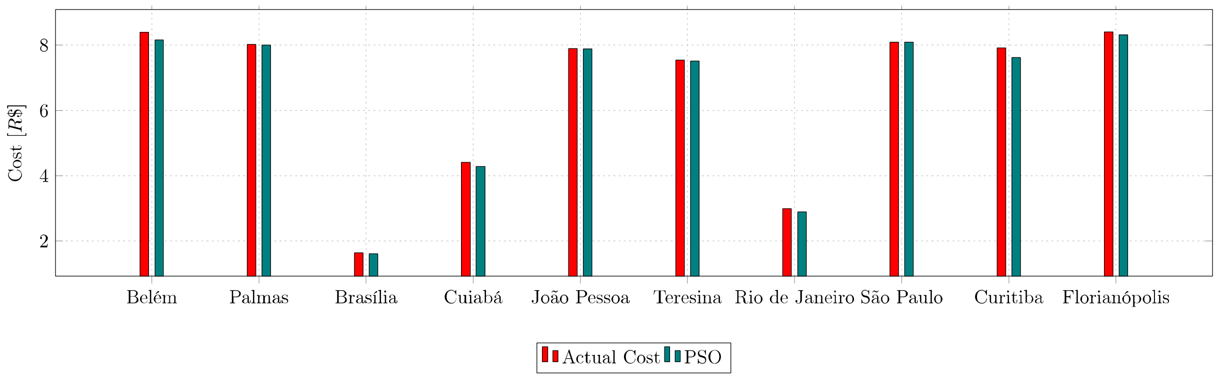

Figure 36 – Cost of Electricity by Family on the Day of the Highest Energy Consumption (Profile 3).

Table 41 and Figure 37 show a comparison of the results by EMC using the PSO to solve the DR optimization model in order to minimize the cost associated with the consumption of electric energy of each family on the day of lowest energy consumption. The family living in Cuiabá-MT obtained the greatest reduction in the cost associated to the electric energy consumption, when compared to the other families in the cities of Belém-PA, Palmas-TO, Brasília-DF, Teresina-PI, Rio de Janeiro-RJ, São Paulo-SP, Curitiba-PR, and Florianópolis-SC, from R$ 1.84 to R$ 1.61.

Table 41 – Cost of Electricity by Family on the Day of the Lowest Energy Consumption (Profile 3).

Family	Cities	Cost Without DR (R$)	Cost With DR (R$)	Reduction (%)
I	Belém-PA	2.39	2.11	11.72
II	Palmas-TO	4.60	4.36	5.22
III	Brasília-DF	1.49	1.46	2.01
IV	Cuiabá-MT	1.84	1.61	12.50
V	João Pessoa-PB	2.52	2.47	1.98
VI	Teresina-PI	4.72	4.66	1.27
VII	Rio de Janeiro-RJ	1.90	1.87	1.58
VII	São Paulo-SP	2.36	2.12	10.17
IX	Curitiba-PR	2.73	2.71	0.73
X	Florianópolis-SC	2.18	2.07	5.05

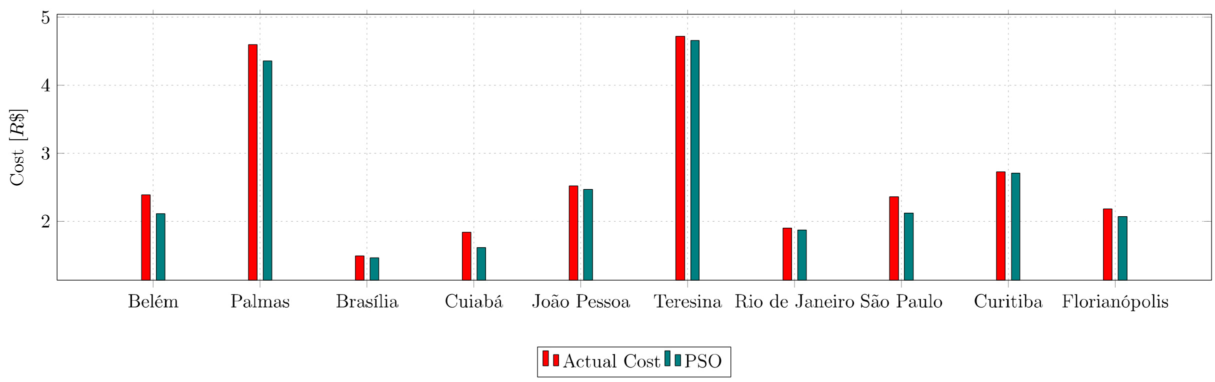

Figure 37 – Cost of Electricity by Family on the Day of the Lowest Energy Consumption (Profile 3).

Table 42 and Table 43 displays the results for the inconvenience level of the end consumers for the use of their home appliances on the days of the highest and lowest electric energy consumption. Thus, families living in Belém-PA (inconvenience: 232) and Palmas-TO (inconvenience: 203) had the worst rates of inconvenience.

Table 42 – Inconvenience on the Day of the Highest Energy Consumption (Profile 3).

Family	Cities	Inconvenience
I	Belém-PA	232
II	Palmas-TO	177
III	Brasília-DF	219
IV	Cuiabá-MT	199

V	João Pessoa-PB	192
VI	Teresina-PI	188
VII	Rio de Janeiro-RJ	216
VIII	São Paulo-SP	167
IX	Curitiba-PR	230
X	Florianópolis-SC	183

Table 43 – Inconvenience on the Day of the Lowest Energy Consumption (Profile 3).

Family	Cities	Inconvenience
I	Belém-PA	112
II	Palmas-TO	203
III	Brasília-DF	162
IV	Cuiabá-MT	176
V	João Pessoa-PB	202
VI	Teresina-PI	148
VII	Rio de Janeiro-RJ	170
VIII	São Paulo-SP	189
IX	Curitiba-PR	158
X	Florianópolis-SC	184

Also, a comparative analysis was verified the EMC efficiency in the load scheduling process using the GA, PSO and LINGO optimization techniques (Appendix B) to minimize the cost related to the electric energy consumption of households in each city. Figure 38 to Figure 43, Table 44 and Table 45, provide a summary of all the results in the optimization process involving load scheduling in the residents on the highest and lowest energy consumption days in the year 2016 using GA, PSO and LINGO.

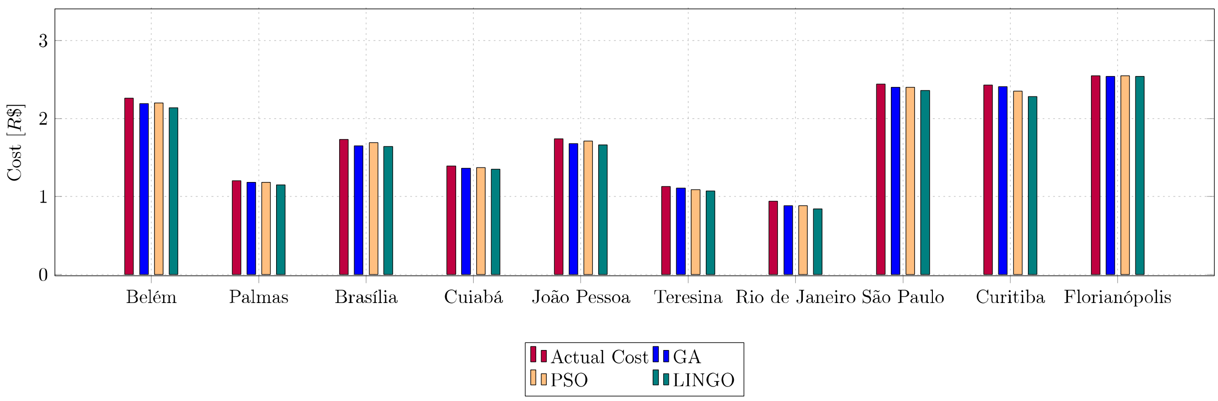

Figure 38 – Profile 1: Comparison Between Actual Cost, GA, PSO and LINGO: Cost with DR on the Highest Electricity Consumption Day

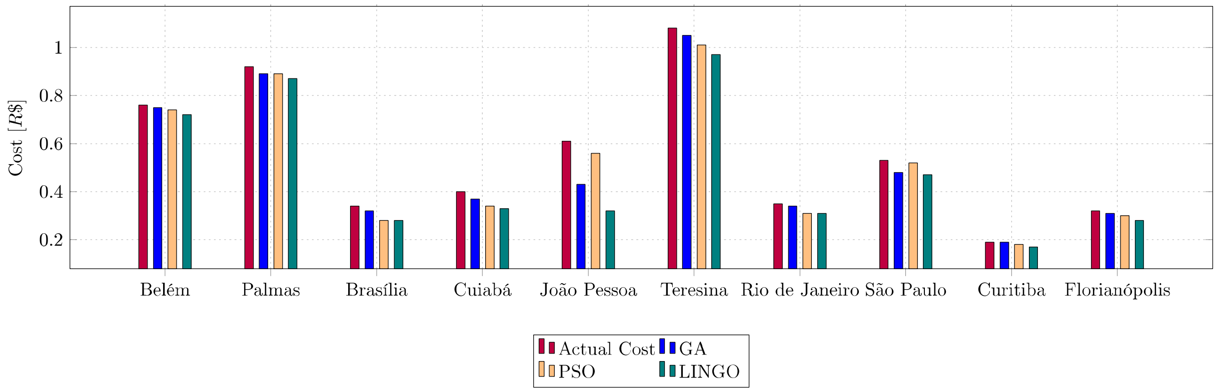

Figure 39 – Profile 1: Comparison Between Actual Cost, GA, PSO, and LINGO: Cost with DR on the Lowest Electricity Consumption Day

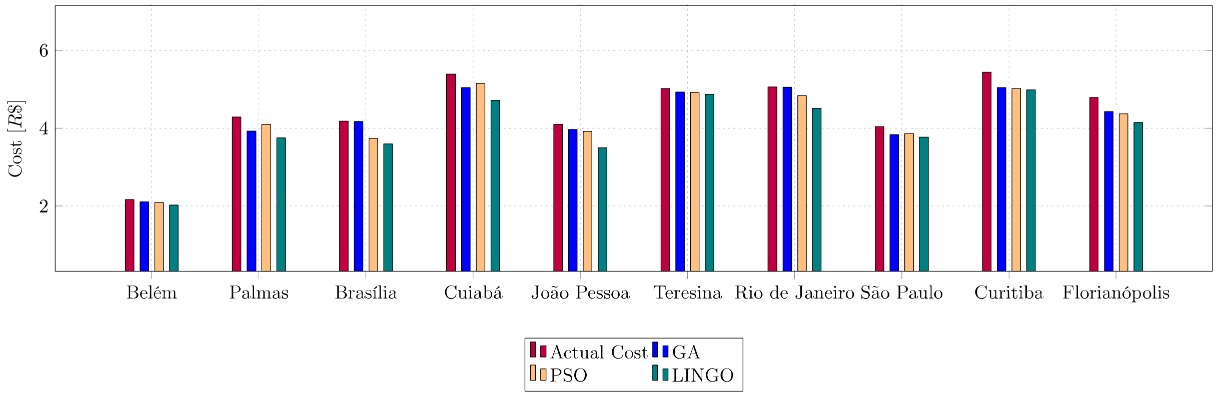

Figure 40 – Profile 2: Comparison Between Actual Cost, GA, PSO and LINGO: Cost with DR on the Highest Electricity Consumption Day

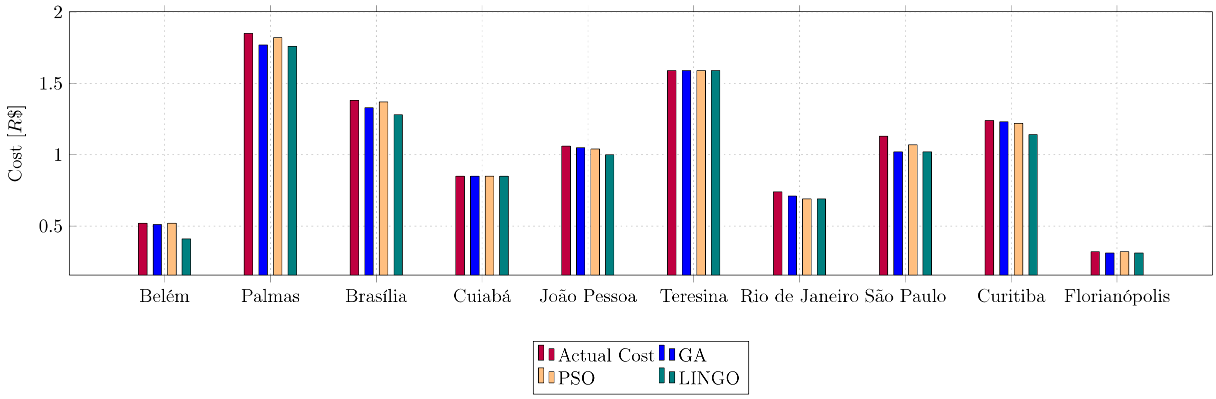

Figure 41 – Profile 2: Comparison Between Actual Cost, GA, PSO, and LINGO: Cost with DR on the Lowest Electricity Consumption Day

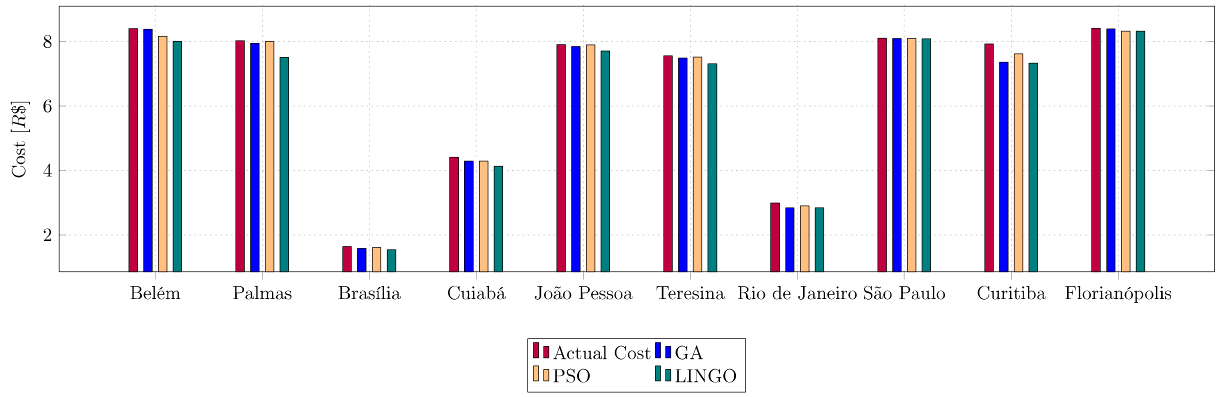

Figure 42 – Profile 3: Comparison Between Actual Cost, GA, PSO and LINGO: Cost with DR on the Highest Electricity Consumption Day

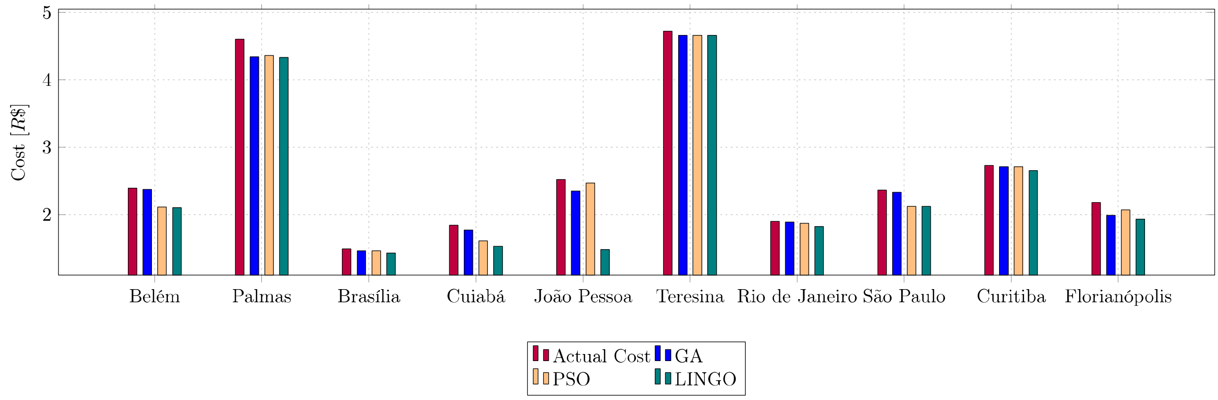

Figure 43 – Profile 3: Comparison Between Actual Cost, GA, PSO, and LINGO: Cost with DR on the Lowest Electricity Consumption Day

Table 44 and Table 45 illustrate that EMC using the LINGO, GA and PSO optimization techniques manages to minimize the total cost of electricity for Profiles 1, 2 and 3 on the highest and lowest energy consumption days, and the reductions were 10.64%, 14.63%, and 7.45%, as well as 47.54%, 21.15% and 41.27%, respectively per profile.

Table 44 – Comparison Between Actual Cost, GA, PSO, and LINGO on the Day of the Highest Energy Consumption.

		Cost Without DR (R$)	GA		PSO		LINGO	
			Cost with DR (R$)	Reduction (%)	Cost with DR (R$)	Reduction (%)	Cost with DR (R$)	Reduction (%)
Belém-PA	**Profile 1**	2.26	2.19	3.10	2.20	2.65	2.14	5.31
	Profile 2	2.17	2.11	2.76	2.09	3.69	2.03	6.45
	Profile 3	8.40	8.38	0.24	8.16	2.86	8.00	4.76
Palmas-TO	**Profile 1**	1.20	1.18	1.67	1.18	1.67	1.15	4.17
	Profile 2	4.29	3.93	8.39	4.10	4.43	3.75	12.59
	Profile 3	8.02	7.94	1.00	8.00	0.25	7.50	6.48
Brasília-DF	**Profile 1**	1.73	1.65	4.62	1.69	2.31	1.64	5.20
	Profile 2	4.18	4.17	0.24	3.74	10.53	3.60	13.88
	Profile 3	1.64	1.58	3.66	1.61	1.83	1.54	6.10
Cuiabá-MT	**Profile 1**	1.39	1.36	2.16	1.37	1.44	1.35	2.88
	Profile 2	5.39	5.04	6.49	5.15	4.45	4.71	12.62
	Profile 3	4.41	4.29	2.72	4.29	2.72	4.13	6.35
João Pessoa-PB	**Profile 1**	1.74	1.68	3.45	1.71	1.72	1.66	4.60
	Profile 2	4.10	3.97	3.17	3.92	4.39	3.50	14.63
	Profile 3	7.90	7.84	0.76	7.89	0.13	7.70	2.53
Teresina-PI	**Profile 1**	1.13	1.11	1.77	1.09	3.54	1.07	5.31
	Profile 2	5.02	4.93	1.79	4.92	1.99	4.87	2.99
	Profile 3	7.55	7.48	0.93	7.52	0.40	7.31	3.18
Rio de Janeiro-RJ	**Profile 1**	0.94	0.88	6.38	0.88	6.38	0.84	10.64
	Profile 2	5.06	5.05	0.20	4.84	4.35	4.51	10.87
	Profile 3	2.99	2.84	5.02	2.90	3.01	2.84	5.02
São Paulo-SP	**Profile 1**	2.44	2.40	1.64	2.40	1.64	2.36	3.28
	Profile 2	4.04	3.84	4.95	3.86	4.46	3.77	6.68
	Profile 3	8.10	8.09	0.12	8.09	0.12	8.08	0.25
Curitiba-PR	**Profile 1**	2.43	2.41	0.82	2.35	3.29	2.28	6.17
	Profile 2	5.44	5.04	7.35	5.02	7.72	4.99	8.27

	Profile 3	7.92	7.36	7.07	7.62	3.79	7.33	7.45
Florianópolis-SC	**Profile 1**	2.55	2.54	0.39	2.54	0.39	2.54	0.39
	Profile 2	4.79	4.43	7.52	4.37	8.77	4.15	13.36
	Profile 3	8.41	8.39	0.24	8.32	1.07	8.32	1.07

Table 45 – Comparison Between Actual Cost, GA, PSO, and LINGO on the Day of the Lowest Energy Consumption.

		Cost Without DR (R$)	**GA**		**PSO**		**LINGO**	
			Cost With DR (R$)	**Reduction (%)**	**Cost With DR (R$)**	**Reduction (%)**	**Cost With DR (R$)**	**Reduction (%)**
Belém-PA	**Profile 1**	0.76	0.75	1.32	0.74	2.63	0.72	5.26
	Profile 2	0.52	0.51	1.92	0.49	5.77	0.41	21.15
	Profile 3	2.39	2.37	0.84	2.11	11.72	2.10	12.13
Palmas-TO	**Profile 1**	0.92	0.89	3.26	0.89	3.26	0.87	5.43
	Profile 2	1.85	1.77	4.32	1.82	1.62	1.76	4.86
	Profile 3	4.60	4.34	5.65	4.36	5.22	4.33	5.87
Brasília-DF	**Profile 1**	0.34	0.32	5.88	0.28	17.65	0.28	17.65
	Profile 2	1.38	1.33	3.62	1.37	0.72	1.28	7.25
	Profile 3	1.49	1.46	2.01	1.46	2.01	1.43	4.03
Cuiabá-MT	**Profile 1**	0.40	0.37	7.50	0.34	15.00	0.33	16.55
	Profile 2	0.8524	0.84	1.18	0.84	1.18	0.8522	0.02
	Profile 3	1.84	1.77	3.80	1.61	12.50	1.53	16.85
João Pessoa-PB	**Profile 1**	0.61	0.43	29.51	0.56	8.20	0.32	47.54
	Profile 2	1.06	1.05	0.94	1.04	1.89	1.00	5.66
	Profile 3	2.52	2.35	6.75	2.47	1.98	2.18	13.49
Teresina-PI	**Profile 1**	1.08	1.05	2.78	1.01	6.48	0.97	10.19
	Profile 2	1.59	1.55	2.52	1.58	0.63	1.58	0.63
	Profile 3	4.72	4.66	1.27	4.66	1.27	4.66	1.27
Rio de Janeiro-RJ	**Profile 1**	0.35	0.34	2.86	0.31	11.43	0.31	11.43
	Profile 2	0.74	0.71	4.05	0.69	6.76	0.69	6.76

	Profile 3	1.90	1.89	0.53	1.87	1.58	1.82	4.21
São Paulo-SP	**Profile 1**	0.53	0.48	9.43	0.52	1.89	0.47	11.32
	Profile 2	1.13	1.02	9.73	1.07	5.31	1.02	9.73
	Profile 3	2.36	2.33	1.27	2.12	10.17	2.12	10.17
Curitiba-PR	**Profile 1**	0.19	0.18	5.26	0.18	5.26	0.17	10.53
	Profile 2	1.24	1.23	0.81	1.22	1.61	1.14	8.06
	Profile 3	2.73	2.71	0.73	2.71	0.73	2.65	2.93
Florianópolis-SC	**Profile 1**	0.32	0.31	3.13	0.30	6.25	0.28	12.50
	Profile 2	0.32	0.31	3.13	0.30	6.25	0.31	3.13
	Profile 3	2.18	1.99	8.72	2.07	5.05	1.93	11.47

4.3 Experimental Scenario 2 (Multi-Objective)

In this scenario, Equation (13) of the DR optimization model (Section 3.2) becomes an objective function in order to minimize the inconvenience level for the optimized scheduling of the home appliances for the end consumers. Thus, the DR optimization model has two objective functions (f_1 and f_2) that are responsible for minimizing the cost associated with the electric energy consumption as well as minimizing the inconvenience level for the end consumers, respectively. Therefore, in this section, the results of the computational simulations obtained through the EMC using the NSGA-II optimization technique are presented in order to solve the DR multi-objective optimization problem described in Section 3.2.

4.3.1 Optimization Process by NSGA-II

Three (03) different profiles of electric power consumption were used for the simulations (Profile 1 – a single adult; Profile 2 – two adults; and Profile 3 – two adults with three children). These profiles were provided by the LPG (PFLUGRADT, 2016) tool for 15 Brazilian families living in the cities of Belém-PA, Teresina-PI, Cuiabá-MT, Florianópolis-SC, and São Paulo-SP, with 3 family per city, located in the North, Northeast, Midwest, South and Southeast regions of Brazil, respectively. Also, the profile had different numbers of home appliances: Profile 1 (23 appliances), Profile 2 (29 appliances) and Profile 3 (33 appliances), totalling 425 appliances for analysis. Table 46 shows the load profiles and the different categories of the home appliances.

Table 46 – Profiles and Categories of Home Appliances.

Profile	Categories	Home Appliances
1	A_I	Light 100 W, 20 W and 60 W, SAT-Receiver, TV, Playstation, Laptop, CD/DVD Player, Computer, DVB-T Receiver, Router, Computer Screen.
	A_{II}	Wine Cellar, Steam Iron, Food Multiprocessor, Microwave, Washing Machine, Electric Kettle, Nespresso Coffee Machine.
	A_{III}	Refrigerator, Air Conditioning, Electric Heater, Freezer.
2	A_I	Light 100 W, 20 W, and 60 W, SAT-Receiver, TV, Cell Phone Charging, Microsoft Xbox, Laptop, CD/DVD Player, Computer, DVB-T Receiver, Router, Computer Screen, Kitchen Radio.
	A_{II}	Wine Cellar, Steam Iron, Hair Dryer, Electric Stove, Microwave, Juicer, Washing Machine, Toaster, Electric Kettle, Nespresso Coffee Machine.
	A_{III}	Refrigerator, Air Conditioning, Electric Heater, Freezer, Dryer.
3	A_I	Light 100 W, 20 W, and 60 W, SAT-Receiver, TV, Cell Phone Charging, Playstation, Microsoft Xbox, Laptop, CD/DVD Player, Computer, Home Cinema System, DVB-T Receiver, Router, Computer Screen, Kitchen Radio.

	A_{II}	Wine Cellar, Steam Iron, Hair Dryer, Electric Razor, Electric Stove, Electronic Hometrainer, Microwave, Juicer, Washing Machine, Toaster, Electric Kettle, Nespresso Coffee Machine.
	A_{III}	Refrigerator, Air Conditioning, Electric Heater, Freezer, Dryer.

The total time horizon in this study is given as $T = 24h$. Each time interval t means one hour and $t \in T$ such that: $T = \{1h, 2h \dots 24h\}$ for each family between January 1st and December 31st, 2016. Other data used in the evaluations were the dynamic price of electricity. The multi-objective DR model used here allows electricity prices from studies that use forecasts or price history values to be used. Price information is an input parameter, and so the model is not restricted to the prices of any specific country or location. In such cases, RTP is considered to be the incorporated tariff. Figure 44 was created by the authors to show the price per unit power consumption at each sub-interval for an energy-intensive day (December 24th, 2016) of Profile 2 in Palmas-TO.

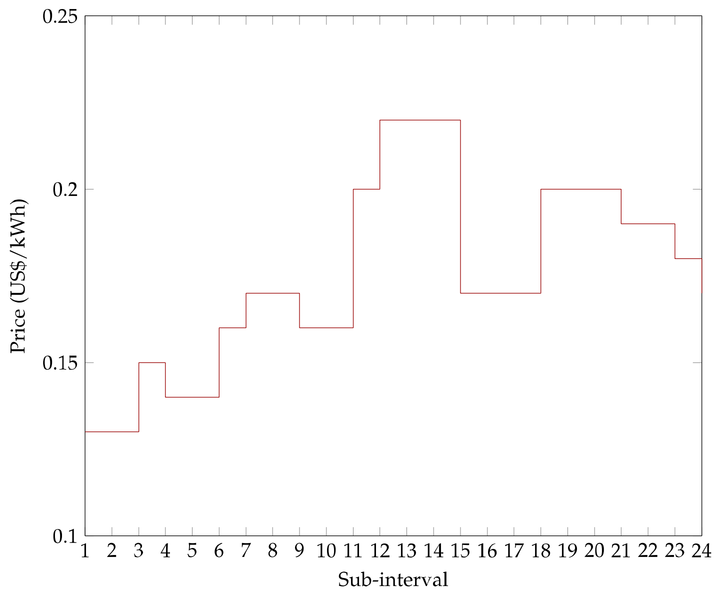

Figure 44 – Price Per Unit Power Consumption.
(VERAS *et al.*, 2018a)

The DR model used the parameters in NSGA-II in Table 47 for validation purposes. The values of the parameter were obtained via simulations with a control map, which is a series of tests with different configurations applied to the NSGA-II. The NSGA-II indicates the best configuration to overcome the multi-objective problem. Other parameters were used as shown in Table 2.

Table 47 – NSGA-II Parameters.

Parameter	Value
Population size	500
Maximum number of iterations	1000
Selection method	Tournament (3)
Crossover method	Single Point
Crossover probability	85%
Mutation method	Bit Flip
Mutation probability	1%

The values first used for these parameters were based on a definition required by the consumers and the utility. Brazil has different and distinct climatic characteristics; for example, in the south and southeast regions, certain periods of the year have relatively low temperatures and therefore air conditioners are not used with much frequency; on the other hand, the north and northeast of the country are subtropical, and the climate is divided into dry and rainy periods but with high temperatures all year round. Consequently, air conditioners are used much more frequently. Each city has its distinct *mdc* value due to the different locations within Brazil and the families in this study have different energy consumption profiles. Consequently, these differences affect the final power consumption of each family differently.

The results obtained in the computational simulations regarding the impact of HEMS using the multi-objective optimization model of DR for different profiles of electric energy consumption considers 02 aspects: (1) the cost of electricity and (2) the level of satisfaction/comfort of end consumers. In the following is a breakdown of the results for these three different profiles. The analysis showed that the best solution is the cost minimization objective (f_1, defined by Equation (12) in Section 3.2), indicated by the letter ***A*** in Figure 45, which presents the Optimal Pareto Frontier reached with the experiments.

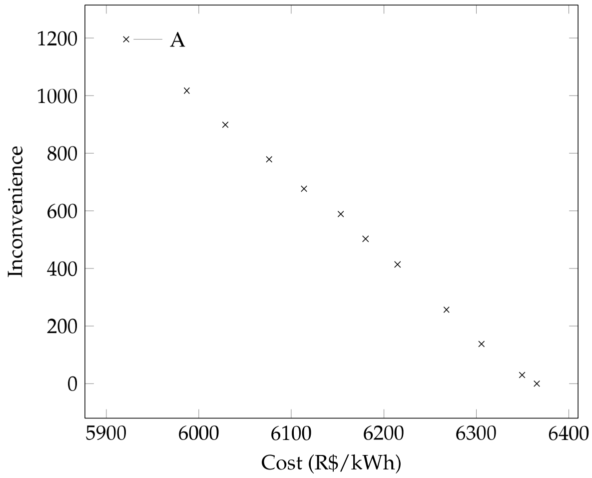

Figure 45 – Optimal Pareto Frontier.
(VERAS *et al.*, 2018a)

Profile 1 – a single adult

Table 48 and Figure 46 gives a summary of the electricity cost for each family in Profile 1. Thus, the family residing in Teresina-PI managed to obtain a greater reduction compared to the other families, with the cost dropping from R$ 200.42 to R$ 183.22.

Table 48 – Reduction of Electricity Costs per Family in Profile 1 for Each City.

Family	Cities	Without DR (R$)	With DR (R$)	Reduction (%)	Reduction (R$)
I	Belém-PA	175.95	167.03	5.07	8.92
II	Cuiabá-MT	175.62	162.59	7.42	13.03
III	Florianópolis-SC	171.14	159.04	7.07	12.10
IV	São Paulo-SP	174.24	163.46	6.19	10.79
V	Teresina-PI	200.42	183.22	8.58	17.20

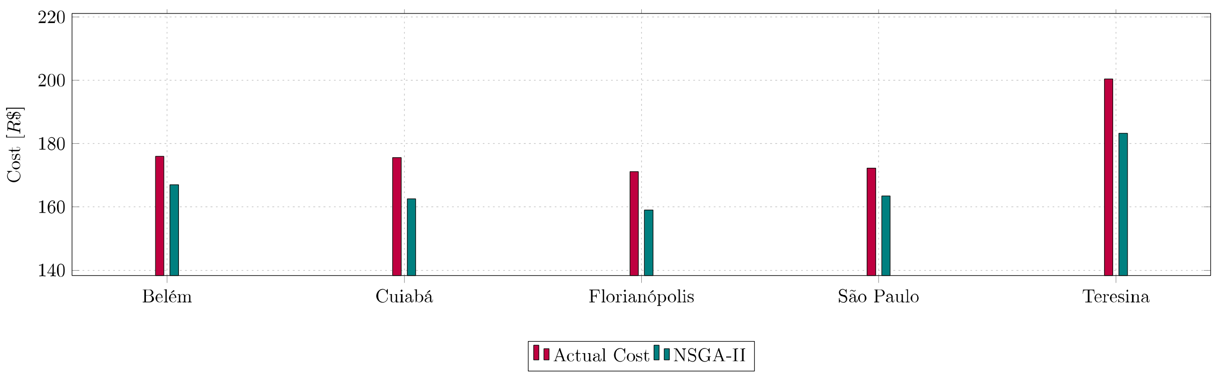

Figure 46 – Reduction of Electricity Costs Per Family in Profile 1 for Each City.
(VERAS *et al.*, 2018a)

The Table 49 summarizes the results for the inconvenience and *Trade-off*. The inconvenience and trade-off values show that the family residing in Teresina-PI had the highest *Trade-off* value which was 0.12, and this is equivalent to a R$ 0.12 reduction per unit of inconvenience caused to the end consumer.

Table 49 – Inconvenience and *Trade-off* analysis in Profile 1.

Family	Cities	Inconvenience Caused	Trade-off
I	Belém-PA	42	0.06
II	Cuiabá-MT	43	0.09
III	Florianópolis-SC	39	0.09
IV	São Paulo-SP	40	0.08
V	Teresina-PI	41	0.12

Profile 2 – two adults

Table 50 and Figure 47 present the results obtained for the cost of electric energy consumption for each family, considering the usage profiles of their home appliances. The results were acquired using LPG (Cost Without DR (R$)) and the technique of optimization (Cost with DR (R$)) using the DR model presented in this work. Thus, the family living in Teresina-PI compared to the other families in the other cities (Belém-PA, Cuiabá-MT, Florianópolis-SC and São Paulo-SP) obtained the largest cost reduction: dropping from R$ 346.44 to R$ 316.47.

Table 50 – Reduction of Electricity Costs per Family in Profile 2 for Each City.

Family	Cities	Without DR (R$)	With DR (R$)	Reduction (%)	Reduction (R$)
I	Belém-PA	321.24	304.98	5.06	16.26
II	Cuiabá-MT	341.09	315.64	7.46	25.45
III	Florianópolis-SC	294.62	273.79	7.07	20.83
IV	São Paulo-SP	310.34	290.75	6.31	19.59
V	Teresina-PI	346.44	316.47	8.65	29.97

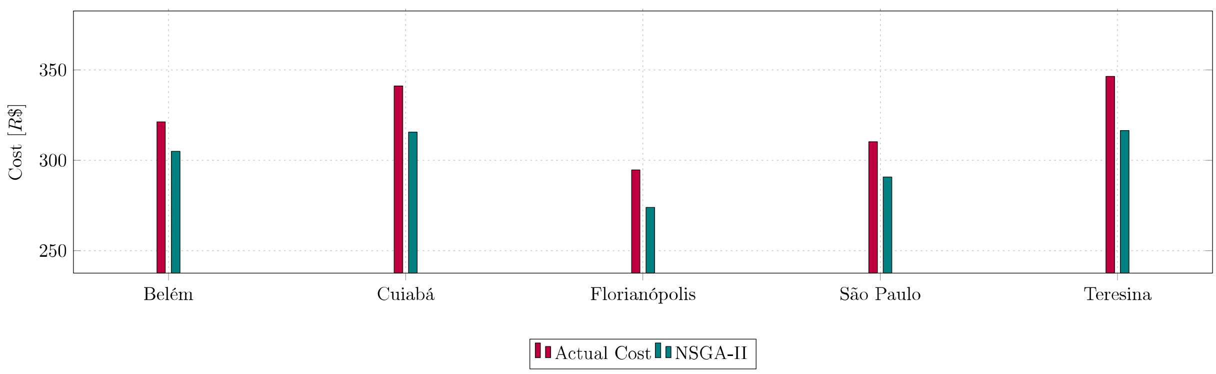

Figure 47 – Reduction of Electricity Costs Per Family in Profile 2 for Each City (VERAS *et al.*, 2018a)

Based on the results obtained, the *Trade*-off solution was calculated, that is, the relation between each unit of inconvenience caused to an end consumer and the reduction attributed to it, which results in the total reduction (in R$) obtained with each unit of inconvenience caused. Thus, the highest *Trade*-off value found was 0.40 for the family located in Teresina-PI, which is equivalent to a reduction of R$ 0.40 per unit of inconvenience caused to the end consumer. Table 51 shows a summary of the results for the inconvenience and *Trade*-off simulations for each family resident in Belém-PA, Cuiabá-MT, Florianópolis-SC, São Paulo-SP and Teresina-PI.

Table 51 – Inconvenience Analysis and *Trade-off* in Profile 2.

Family	Cities	Inconvenience Caused	Trade-off
I	Belém-PA	72	0.23
II	Cuiabá-MT	76	0.33
III	Florianópolis-SC	70	0.30
IV	São Paulo-SP	73	0.27
V	Teresina-PI	75	0.40

Profile 3 – two adults with three Children

The results show that the family living in Teresina-PI reduced the total electricity cost from R$ 874.43 to R$ 799.14. Thus, the family living in Teresina-PI had the highest values related to cost minimization associated with the consumption of electric energy compared to other families in the cities of Belém-PA, Cuiabá-MT, Florianópolis-SC and São Paulo-SP. Table 52 and Figure 48 shows a summary of the results achieved for Profile 3.

Table 52 – Reduction of Electricity Costs per Family in Profile 3 for Each City.

Family	Cities	Without DR (R$)	With DR (R$)	Reduction (%)	Reduction (R$)
I	Belém-PA	756.85	718.40	5.08	38.45
II	Cuiabá-MT	799.98	740.14	7.48	59.84
III	Florianópolis-SC	697.30	647.09	7.20	50.20
IV	São Paulo-SP	726.01	679.76	6.37	46.25
V	Teresina-PI	874.43	799.14	8.61	75.29

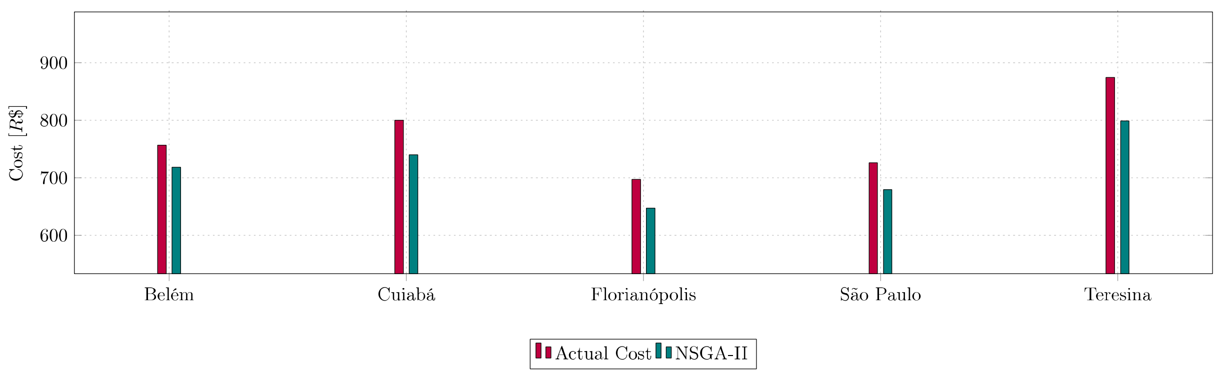

Figure 48 – Reduction of Electricity Costs Per Family in Profile 3 for Each City. (VERAS *et al.*, 2018a)

The inconvenience and *Trade-off* analysis show that the family resident in Teresina-PI obtained the highest *Trade-off* value with a total of 0.60, which is equivalent to R$ 0.60 reduction per unit of inconvenience caused to the end consumer. Table 53 shows a summary of the results obtained in the study for the inconvenience and the *Trade-off* for the families in their respective cities.

Table 53 – Inconvenience and *Trade-off* Analysis in Profile 3.

Family	Cities	Inconvenience Caused	Trade-off
I	Belém-PA	125	0.31
II	Cuiabá-MT	127	0.47
III	Florianópolis-SC	123	0.41
IV	São Paulo-SP	124	0.37
V	Teresina-PI	126	0.60

4.3.1.1 Statistical Analysis

Also, the results from the experiments with scheduling for the home appliances were analyzed by three performance metrics: Diversity, Coverage, and Hypervolume. Diversity (SCHOTT; OH, 1995) measures the number of different solutions given by an algorithm in a search space between extreme solutions (maximum/minimum solutions of each objective function). Thus, a great number of solutions found in the search space means there are a great number of options available for decision-making.

The Coverage (metric C) is used to evaluate the optimal approach capability of the solutions, which is the (theoretical) distance between the current Pareto Frontier and the theoretical optimal Pareto Frontier. Thus, based on its theoretical properties (ZITZLER; THIELE, 1999), coverage ensures a space of solutions closer to the theoretical optimum to solve the DR problem.

The Hypervolume (HV) is a performance metric that calculates the volume of the objective space among the set of solutions found and a reference point; here, the reference point was the nadir point, which is the vector whose elements are the worst values of each criterion of the multi-objective problem (LU; ANDERSON-COOK, 2013; ZITZLER, E.; BROCKHOFF, D.; THIELE, 2007). The higher the HV value is, the better the convergence, extension, and uniformity (ZITZLER; THIELE, 1999).

Diversity

The spacing metric (SCHOTT; OH, 1995) was used to calculate the Diversity, which is given by s:

$$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(\bar{d} - d_i\right)^2} \tag{21}$$

where $d_i = min_j \sum_{a=1}^{M}\{|f_a^i(x) - f_a^j(x)|\}, i, j = 1, 2, 3, \dots, n, i \neq j$. $\bar{d}$ represents the average values of d_i, M is the number of objectives of the problem and n is the number of solutions.

The closer the value of s is to zero, the greater the similarity between the solutions will be, within the analyzed set. Thus, there will be a lower diversity of solutions (SCHOTT; OH, 1995).

Coverage

The coverage ratio for two sets of solutions is compared by the metric C. The number of points in set B dominated by set A over the total number of points in set B is represented by $C(A, B)$. Equation (22) demonstrates metric C:

$$C(A, B) = \frac{|\{x \in B \mid \exists y \in A : y\ dominates\ x\}|}{|B|} \tag{22}$$

If the value $C(A, B) = 1$, it means that all points in B are dominated by A or equal to the points contained in A. In contrast, if $C(A, B) = 0$, it indicates that none of the points in B are dominated by the set A. Thus, it should be noted that $C(A, B)$ and $C(B, A)$ should be considered because $C(A, B) \neq 1 - C(B, A)$ (ZITZLER; THIELE, 1999). In the simulations, A will be composed of the solutions of the DR multi-objective model presented in this work using the NSGA-II, while B will be composed of the solutions of the random search algorithm.

Hypervolume

The Hypervolume (HV) was calculated to evaluate the performance of the results from the DR model. An HV is a performance metric that calculates the volume of the objective space among the set of solutions found and a reference point; here, the reference point was the nadir point, which is the vector whose elements are the worst values of each criterion of the multi-objective problem (LU; ANDERSON-COOK, 2013; ZITZLER, E.; BROCKHOFF, D.; THIELE, 2007). The higher the HV value is, the better the convergence, extension and uniformity are (ZITZLER; THIELE, 1999).

Hypervolume Indicator

Various authors (ZITZLER, E.; BROCKHOFF, D.; THIELE, 2007) consider that hypervolume indicators are based on polytope volumes and/or hypercubes. Also, the Pareto dominance is considered to be the underlying preference.

Equation (23) shows that the attainment function demonstrates that each objective vector in the objective space $Z = [0,1]^n$ is weakly dominated by the result of some multi-objective optimizer (ZITZLER, E.; BROCKHOFF, D.; THIELE, 2007).

Definition 1 (attainment function of an objective vector set). If $A \in \Omega$, then the attainment function αA: $[0,1]^n \rightarrow \{0,1\}$ for A is

$$\alpha A(z) := \begin{cases} 1 & if\ A \gtrsim \{z\} \\ 0 & else \end{cases} \tag{23}$$

for $z \in Z$.

Attainment function concepts can give definitions of hypervolume indicators. The hypervolume is the volume of the objective space surrounded by the attainment function and the axes (ZITZLER, E.; BROCKHOFF, D.; THIELE, 2007).

Definition 2 (hypervolume indicator). The hypervolume indicator I_H^* and a reference point $(0, \ldots, 0)$ are described by attainment function as thus:

$$I_H^*(A) := \int_{(0,\ldots,0)}^{(1,\ldots,1)} \alpha A(z) dz \tag{24}$$

where A is an objective vector set among all possible objective vector set: $\Omega := 2^Z$ (ZITZLER, E.; BROCKHOFF, D.; THIELE, 2007).

The authors in (ZITZLER *et al.*, 2003) state that HV is the only unary metric that can evaluate if one set of solutions S is not worse than another S set. Thus, a set of solutions is Pareto optima only when the HV is maximized and vice versa. Thus, the main characteristic of HV is that it is compatible with the dominance of Pareto; if one population of Pareto dominates another, then this one has an HV greater than the dominated one. In addition, it does not need the real Pareto frontier of the problem in its calculation (ZITZLER *et al.*, 2003; ZITZLER; THIELE, 1999).

4.3.1.1.1 Statistical Results

Simulations with a random search algorithm are used to calculate the Coverage metric. A random search algorithm is a genetic algorithm (GA) (HOLLAND, 1975), with a random selection method that does not use heuristics, called random GA, and is compared to the NSGA-II optimization technique. Thus, the C (ZITZLER; THIELE, 1999) metric is used to determine which of the techniques (NSGA-II or random GA) has the best coverage. The Hypervolume (HV) metric (ZITZLER et al., 2003; ZITZLER; THIELE, 1999) is used to evaluate the overall performance of the two techniques (NSGA-II or random GA) in more detail. Both NSGA-II and random GA were performed 1000 executions to reduce the impact of their stochastic nature and to obtain the values to be used in the statistical analysis.

The results of the study with the NSGA-II optimization technique were compared with the values from the random GA in order to validate the correctness of the algorithm (sanity check). The values of the spacing metric showed that the NSGA-II (minimum 14.32 and maximum 18.11) had a greater diversity of solutions than the random GA (minimum 10.25 and maximum 15.96) Therefore, the NSGA-II had a better coverage of the search space, and this translates into a better comprehension of the objectives considered in the problem.

In the metric C the values obtained for both $C(A,B)$ and $C(B,A)$ indicate that, in all cases, the Pareto frontier solutions found by the NSGA-II completely dominated the frontier solutions of Pareto found by random GA. Additionally, it utilized the time spent (milliseconds) in solving the problem as another evaluation metric. This result shows that the NSGA-II presents better solutions than the random GA, considering the Pareto frontier of both techniques.

On validating the results of space and coverage metrics the analysis of the Hypervolume values found in the simulations indicates a significantly better general performance of NSGA-II (minimum 0.55 and maximum 0.63) about random GA (minimum 0.34 and maximum 0.45). This information indicates that the results of the computer simulations obtained by the NSGA-II completely dominate the values reached by random GA reflecting its better performance, regarding convergence and extension, of the solution considering the search space (ZITZLER; THIELE, 1999).

Finally, it can be seen in the statistical results that the NSGA-II obtained a minimum execution time of 56 and a maximum of 70, while the Random GA presented a minimum execution time of 60 and a maximum of 77. Therefore, both the NSGA-II and Random GA with these execution times enable the load scheduling to provide a reduction in electricity costs, as well as minimize the inconvenience caused to the end consumers promptly. Table 54 shows the statistical values for the simulations.

Table 54 – Statistical analysis.

Algorithm	Metric	Min	Max	Average	Standard Deviation
NSGA-II	Spacing	14.32	18.11	16.06	1.14
Random GA		10.25	15.96	14.37	1.06
NSGA-II	C (A, B)	1	1	1	0
Random GA					
NSGA-II	C (B, A)	0	0	0	0
Random GA					
NSGA-II	HV	0.55	0.63	0.58	0.01
Random GA		0.34	0.45	0.39	0.01
NSGA-II	Runtime ($x10^3$)	56	70	65	0.5
Random GA		60	77	70	0.5

4.4 Final Considerations

In this chapter, the experiments scenarios (mono and multi-objective), distinct electricity consumption profiles, different home appliance categories, the parameters and the statistical metrics were used to validate the solutions obtained during the computational simulations were presented.

The results obtained by the HEMS through its operational core (EMC) using LINGO, GA, PSO, and NSGA-II techniques were promising. In the mono and multi-objective scenarios, HEMS was able to achieve a good level of feasible solutions to DR problems that involved cost minimization related to energy consumption as well as minimizing the inconvenience level for end consumers in the residential setting studied in this thesis. Thus, the DR optimization model achieved the goal of reducing the total cost of electricity to end consumers by programming the use of home appliances.

It is worth mentioning that obtaining the largest reductions in the cost associated with electricity consumption indicates that the load (re)scheduling was distributed throughout the planning horizon for schedules that present the lowest value to be paid for electricity consumption, reaching better results. About the inconvenience, as higher the values are, greater the interference of the DR optimization model will be, in relation to the use of the residential appliances and in the preferences of the final consumers; that is, the load displacements directly affect the standard of energy consumption, obliging the consumer to modify their routine, which is not always pleasant.

Statistical analysis was performed using Diversity, Coverage and Hypervolume metrics to construe the results obtained through the NSGA-II involving load scheduling to minimize the cost associated with energy consumption as well as to minimize the inconvenience level for the consumers.

These computational simulations demonstrated the efficiency of the optimization techniques used to solve the DR problem presented in this thesis. In Appendix B, a comparison of optimization techniques (LINGO, PSO, GA, and NSGA-II) is given in detail, and it highlights some aspects such as the mathematical formulation to be solved, the proposal applied in each technique, the experiment scenarios used in the computational simulations with each technique and, finally, the parameters used by each technique during the experiments.

Chapter 5

CONCLUSIONS AND FUTURE WORKS

This chapter presents the conclusions of this thesis and suggests some possibilities for future works.

5.1 Final Conclusions

Scheduling management of home appliances in smart grids enables the EPS to be more efficient and effective because issues such as power interruptions during peak demands can be minimized. Thus, DR plays a key role in managing energy consumption in order to avoid overloading as well as reducing the cost of electricity for end consumers. However, this optimized operation of home appliances requires an infrastructure capable of scheduling the operating periods of the devices over the planning horizon, and thus reducing the periods of peak demand, and improving the reliability and efficiency of the EPS minimally affecting the satisfaction/comfort of end consumers.

Therefore, this thesis proposes a home energy management system (HEMS) and a multi-objective DR optimization model to manage the scheduling of electrical appliances in residencies, aiming at minimizing the cost associated to the energy consumption, as well as minimizing the inconvenience (dissatisfaction/discomfort) of end consumers.

The performance of the HEMS using the DR optimization model was evaluated through simulations. First, the efficiency of the HEMS was analyzed for cost minimization associated with the consumption of electric energy as well as inconvenience (dissatisfaction/discomfort) minimization of end consumers of the different residential Scenarios. Besides, the HEMS performance was evaluated for the load scheduling of various appliances in order to verify the influence of such appliances to reduce the cost of electricity. Next, through the diversity, coverage and hypervolume metrics, the characteristics of the solutions for the problem of scheduling the home appliances were evaluated.

5.2 Main Contributions

The contributions of this thesis are directly related to the development of HEMS, a system applied to the DR problem that involves the usage management process of residential appliances in order to minimize the cost associated to the electricity consumption and the inconvenience level for the end consumers. Therefore, this section summarizes the main contributions resulting from the research work presented in this thesis.

The first and second contributions of this thesis are two studies of the state of art conducted in an initial phase of this work. The first consists of the study about the conceptualizations related to smart grid and demand response. The second is a literature review of the existing solutions to solve the load scheduling problem considering TOU, RTP and CPP tariff models in order to minimize the cost associated with the consumption of electric energy as well as reduce the inconvenience level to end consumers regarding the use of different categories of home appliances. These contributions are described in Chapter 2.

The third contribution is a solution to manage the use of home appliances through a DR model that aims to minimize the cost associated with the consumption of electric energy for different profiles of energy consumption interfering as little as possible in the satisfaction / comfort level of end consumers. The DR model presented in this thesis was evaluated and validated by the LINGO tool for scenarios which considers geographic positioning and climatic temperatures that vary in 10 Brazilian capitals, distributed by the 05 regions of the country. This contribution can be found in Chapter 4.

The fourth contribution is a solution (a mono-objective DR optimization model) for residential consumers based on real-time pricing of electricity (RTP) to minimize the cost of electricity related to consumption. The computer simulations used families that had different profiles of load consumption but the same number of members: 02 working adults and 02 teenagers. These families lived in 05 Brazilian cities (Palmas-TO, Cuiabá-MT, João Pessoa-PB, Rio de Janeiro-RJ e Florianopolis-SC) that are in 05 different regions of the country: North, Midwest, Northeast, Southeast, and South. The proposed optimization model was solved computationally using a genetic algorithm (GA), which determines the programming of home appliances for the entire time horizon. This contribution is in the Chapter 4 and it was published in XIII Simpósio Brasileiro de Automação Inteligente (SBAI) (SILVA *et al.*, 2017).

The fifth contribution is a solution that refers to the development of a mono-objective DR optimization model for residential consumers that considers the real-time pricing of electricity to minimize the costs related to the consumption of electric energy, and it ponders the operational aspects of each home appliance. Computational simulations were applied to an energy consumption profile (family with 02 working adults and 02 teenagers) living in 05 Brazilian cities: Belém-PA, Brasília-DF, Teresina-PI, São Paulo-SP, and Curitiba-PR. It can be found in Chapter 4 and this contribution was published in the International Conference on Systems, Man, and Cybernetics (SMC) (VERAS *et al.*, 2017).

The sixth contribution is also a solution (multi-objective DR optimization model) that applied the real-time pricing of electricity to solve the optimal management problem of residential loads. Its purpose was to minimize both the cost of electricity associated with consumption and the inconvenience (dissatisfaction/discomfort) caused to consumers. The proposed model was formalized as a nonlinear programming problem subjected to a set of constraints related to the electricity consumption and operational aspects about the home appliance categories. The proposal was solved computationally through the Nondominated Sorted Genetic Algorithm (NSGA-II) to determine the new scheduling of home appliances for 02 (two) different residential scenarios (02 adults with 03 children and 01 adults without children). This contribution is in Chapter 4 and it was published in XXII Congresso Brasileiro de Automática (CBA) (VERAS *et al.*, 2018b).

The seventh contribution is a solution that uses the DR model proposed in (VERAS et al., 2017) and analyzed the electricity consumption data from 10 families in the year 2015 in 10 capitals (Belém-PA, Palmas-TO, Brasília-DF, Cuiabá-MT, Teresina-PI, João Pessoa-PB, São Paulo-SP, Rio de Janeiro-RJ, Florianópolis-SC and Curitiba-PR) that are located in the 05 main different regions of Brazilian. This proposal is also in Chapter 4 and it was published in Sustainability Journal (VERAS *et al.*, 2018c).

The eighth contribution is a Home Energy Management System (HEMS) solution based on the studies presented in (VERAS *et al.*, 2017) (VERAS *et al.*, 2017)

(VERAS *et al.*, 2018b) and (VERAS *et al.*, 2018c) to manage the use of home apliances in different scenarios of energy consumption (Scenario 1 - two adults without children; Scenario 2 two adults with three children; Scenario 3 - one adult without children) that validated their efficiency about the planning of the use of the home appliances. Thus, using the NSGA-II technique, the HEMS allows to manage the use of home appliances in order to minimize the cost associated with energy consumption as well as minimize the inconvenience level of consumers. This contribution was published in Sensors International Journal and can be found in Chapter 4 (VERAS *et al.*, 2018a).

5.3 Limitations

Several factors influenced possible limitations to the HEMS proposal in developing, executing and analyzing this work, such as:

1. The insertion of renewable sources of electricity generation, an energy storage system and electric vehicles were not included in the mathematical formulation presented in Chapter 3;
2. A comparative analysis of communication technologies for smart grids and demand response was not performed;
3. The App Mobile, which allows end consumers to monitor the cost and the power consumption of each home appliance and also (re)schedule the use of the loads according to their preferences, has not been implemented;
4. Other tariff models such as TOU were not used during the computational simulations;
5. The experiments were performed in a simulated environment.

5.4 Future Works

Based on the limitations presented in Subsection 5.3, the continuity of the research can be further improved in several directions, as follows:

- To improve the DR optimization model in order to include some features of the microgrids, such as the use of electric vehicles, renewable sources for the generation of electric energy and energy storage systems;
- To use exact methods to solve multi-objective problems in demand response scenarios;

- To conduct a comparative analysis between the communication technologies used in the SGs to determine the best ones for residential scenarios;
- To implement the App Mobile to facilitate the user programming of the home appliances by the end consumers;
- To evaluate the performance of HEMS about the reduction of the cost associated with the electric energy consumption contemplating different tariff models;
- To perform experiments in real environments.

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Appendix

APPENDIX A: SCRIPT LINGO NONLINEAR PROGRAMMING

```
sets:
	periodo/@ole(NomePlanilha.xls)/:custo, load;
	aparelho/@ole(NomePlanilha.xls)/:categoria, e, p, req;
	matriz(periodo, aparelho):DSoA, consreal, consrealbin;
endsets
data:
	custo, dmax, dmin, categoria, e, p, req, rd, ru, mdc, st, et, consreal =
	@ole(NomePlanilha.xls);
enddata
calc:
	@for(matriz(t,i)|consreal(t,i)#EQ#0:consrealbin(t,i)=0);
	@for(matriz(t,i)|consreal(t,i)#GT#0:consrealbin(t,i)=1);
endcalc
!Função objetivo - (1);
[FO]min = @sum(aparelho(i):e(i)*@sum(periodo(t):custo(t)*DSoA(t,i))^2);
@sum(aparelho(i):e(i)*@sum(periodo(t):custo(t)*DSoA(t,i))) = custo_total;
!Restrição - (2);
@for(periodo(t):[DEF_LOAD]@sum(matriz(t,i):DSoA(t,i)*p(i)) = load(t));
@for(periodo(t):[LIMITE_Dt]@bnd(dmin, load(t), dmax));
!Restrição - (3);
@for(periodo(t)|t#LE#et-1:[LIM_MAX_r]@sum(aparelho(i):(DSoA(t,i)-
DSoA(t+1,i))*p(i)) <= rd);
!Restrição - (4);
@for(periodo(t)|t#LE#et-1:[LIM_MIN_r]@sum(aparelho(i):(DSoA(t+1,i)-
DSoA(t,i))*p(i)) <= ru);
!Restrição - (5);
[MDC_]@sum(matriz(t,i):DSoA(t,i)*e(i)) >= mdc;
!Restrição - (6);
@for(aparelho(i)|categoria(i)#EQ#1:[CAT_1]@sum(periodo(t):DSoA(t,i))>=req(i));
!Restrição - (7);
@for(aparelho(i)|categoria(i)#EQ#2:[CAT_2]@sum(periodo(q)|q#LE#et-
req(i)+1:@prod(periodo(t)|t#GE#q#AND#t#LE#req(i)+(q-1):DSoA(t,i)))>=1);
!Restrição - (8);
@for(aparelho(i)|categoria(i)#EQ#3:[CAT_3]@sum(periodo(t)|t#GE#1#AND#t#LE#re
q(i):DSoA(t,i))>=req(i));
!DSoA binária;
@for(matriz(t,i):@bin(DSoA(t,i)));
!uso_bin binária;
@for(matriz(t,i):@bin(consrealbin(t,i)));
!Inconveniência;
@sum(matriz(t,i):(consrealbin(t,i)-DSoA(t,i))^2)=inconv;
!Consumo;
@sum(matriz(t,i):e(i)*DSoA(t,i)) = consum_otimiz;
data:
	@ole(dadoscui.xls) = DSoA, load, custo_total, consrealbin, inconv,
	consum_otimiz;
enddata
```

APPENDIX B: TABLE 55 – COMPARISON BETWEEN THE SIMULATIONS OF DIFFERENT OPTIMIZATION TECHNIQUES (LINGO, PSO, GA E NSGA-II)

<table>
<tr><th rowspan="2">ITEMS</th><th colspan="4">OPTIMIZATION TECNIQUES</th></tr>
<tr><th>LINGO</th><th>PSO</th><th>GA</th><th>NSGA-II</th></tr>
<tr><td rowspan="2">MATHEMATICAL FORMULATION</td><td colspan="3">• Nonlinear programming problem.
✓ Mono-objective:
▪ Minimize the cost associated with energy consumption contemplating the constraints related to electricity consumption and also, restrictions related to the satisfaction/comfort of the end consumers.</td><td rowspan="2">• Multi-objective nonlinear programming problem.
✓ Multi-objective:
▪ Minimize the cost associated with the consumption of electric energy.
▪ Minimize the level of consumer inconvenience regarding the optimized use of home appliances.</td></tr>
<tr><td colspan="3">• The DR model calculates the inconvenience level of consumers about the optimal use of home appliances.</td></tr>
<tr><td>PROPOSAL</td><td colspan="3">• A DR optimization model for residential consumers that considers the real-time price (RTP) of electricity and the operational aspects of home appliances in order to minimize the cost associated with electricity consumption.</td><td>• A home energy management system (HEMS) architecture aims to schedule the use of each home appliance based on real-time electricity price (RTP) and consumer satisfaction/comfort level to ensure stability and safety of EPS.
• HEMS contains the EMC, the operative system core. When installed in residence using the multi-objective DR optimization model presented in this thesis, it manages the use of all the home appliances in order to minimize the cost related to the electric energy consumption as well as the inconvenience level for the consumers. Under these circumstances, EMC guarantees a more economic scenario for all end consumers.</td></tr>
</table>

<table>
<tr>
<td>TEST SCENARIOS</td>
<td colspan="2">• Energy consumption profile:
✓ Profile 1 - a single adult.
✓ Profile 2 - two adults.
✓ Profile 3 - two adults with three children.
• Thirty families are living in 10 capitals located in different regions of Brazil.
• A number of Home Appliances: 870.
• Data (consumption and price): the Year of 2016.</td>
<td>• Scenario 1 - Energy consumption profile:
✓ Two adults e two teenagers.
• 05 families are living in 05 capitals located in different regions of Brazil.
• A number of Home Appliances: 145.
• Data (consumption and price): the Year of 2015.
• Scenario 2: Energy consumption profile:
✓ Profile 1 - a single adult.
✓ Profile 2 - two adults.
✓ Profile 3 - two adults with three children.
• 30 families located in ten capitals located in different regions of Brazil. A number of Home Appliances: 870.
• Data (consumption and price): The Year of 2016.</td>
<td>• Energy consumption profile:
✓ Scenario 1 - 02 adults without children.
✓ Scenario 2 - 02 adults with 03 children.
✓ Scenario 3 – Single adult.
• Fifteen families located in 05 capitals in different regions of Brazil.
• A number of Home Appliances: 425.
• Dataset (consumption and price): the Year 2016.</td>
</tr>
<tr>
<td>PARAMETERS</td>
<td>• Global Solver Options: Use Global Solver.
• NLP Solver Version: Ver 3.0.
• Derivatives (First Order): Solver Decides.
• Strategies: Quadratic Recognition e SLP Directions.</td>
<td>• Population Size: 100
• Interactions: 500
• Particle weight (max/min): 0.9/0.4
• Acceleration Factors (c1/c2): 2/2
• Initial Velocity: 10% of position.</td>
<td colspan="2">• Population Size: 500
• Interactions: 1000
• Crossover Probability: 85%
• Mutation Probability: 1%</td>
</tr>
<tr>
<td>OTHER PARAMETERS</td>
<td colspan="4">• The maximum demand for a time interval (d^{max}): 3 kW
• Minimum demand for a time interval (d^{min}): 0 kW
• Ramping down limit (r^{D}): 1 kWh
• Ram-ping up limit (r^{U})1 kWh</td>
</tr>
</table>