Andreia Melo Carreiro

The role of an Energy Box Aggregator to support *load follows supply* strategies

PhD Thesis in Sustainable Energy Systems supervised by Professor Carlos Alberto Henggeler de Carvalho Antunes and Professor Humberto Manuel Matos Jorge submitted to the Department of Mechanical Engineering, Faculty of Sciences and Technology of the University of Coimbra

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PhD Thesis in Sustainable Energy Systems

In the context of the Energy for Sustainability Initiative of the University of Coimbra and the MIT-Portugal Program

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ABSTRACT

The increasing penetration of renewable generation in the electric power system has been leading to a higher complexity of grid management due to its inherent intermittency, also with impact on the volatility of electricity prices. Setting the adequate operating reserve levels is one of the main concerns of the System Operator, since the integration of a large share of intermittent generation requires an increased amount of reserve that is needed to balance generation and load, assuring the quality of service and the security of the supply. At the same time, energy consumption in households has been steadily growing, representing a significant untapped savings potential due to consumption waste and load flexibility (that is, the possibility of time deferring the use of some loads to optimize consumption, namely in face of dynamic tariffs).

In the Smart Grid context, the involvement of end-users is a key element for the implementation of demand response as a way to enhance the energy efficiency of the electricity infrastructure, also enabling to cope with the intermittency of renewable energy sources. Although the participation of end-users may result in a higher complexity of the system management, it may have a positive impact on mitigating the volatility of electricity prices. End-users may also be an important element in the provision of ancillary services, using demand side resources to offer the system operator additional means to enhance system flexibility, robust planning, constraint management and operation scheduling, therefore contributing to the balance between load and supply under a *load follows supply* strategy. Demand response is seen as an effective and reliable strategy for the successful integration of renewable energy sources, in a perspective of integrated energy resource management, handling the demand curve using load flexibility whenever the system requires it. This embodies the possibility of changing/controlling the load profile by optimally time deferring the use of some equipment by means of energy management systems.

An energy management system aggregator, named Energy Box Aggregator – EBAg, has been designed to operate as an intermediary between individual energy management systems and the System Operator and/or Energy Market, capable of facilitating a load follows supply strategy in a Smart Grid context. The aggregator is aimed to use the flexibility provided by each end-user aggregated into clusters of demand-side resources to satisfy system service requirements, involving lowering or increasing the power requested to the grid throughout a given planning period. This contributes to the balance between load and supply and copes with the intermittency of renewable sources, thus offering an attractive alternative to supply side investments on peak and reserve generation.

For this purpose, a Multi-Objective Optimization model has been developed to maximize the aggregator profits, taking into account revenues from the System Operator and/or Energy Market and payments to end-user clusters, and minimize the inequity between the amounts of load flexibility provided by the clusters to satisfy grid requests. An approach based on coupling a Genetic Algorithm with a Differential Evolution algorithm has been designed to deal with this model. This approach has been then extended to perform a robustness analysis of the solutions.

Keywords: Energy Management Systems, Aggregator, Demand Response, Genetic/Evolutionary Algorithms, Differential Evolution, Multi-Objective Optimization;

Resumo

O aumento da penetração de fontes de energia renováveis no sistema de energia elétrica origina desafios na gestão da rede elétrica, devido ao seu carácter intermitente, bem como volatilidade dos preços da eletricidade. A manutenção dos níveis de reserva operacional adequados é uma das principais preocupações do operador do sistema, uma vez que a integração de uma componente significativa da produção de eletricidade por fontes intermitentes requer uma maior quantidade de reserva necessária para equilibrar a produção e o consumo. Por outro lado, o consumo de eletricidade tem vindo a crescer ao longo dos últimos anos, representando um potencial de poupança ainda não totalmente explorado, através da eliminação de consumo de *standby*, eliminação de desperdícios, bem como da flexibilização do consumo ao longo do tempo.

No contexto das redes inteligentes (*Smart Grids*), o envolvimento dos utilizadores finais é um elemento chave para a implementação de abordagens de resposta dinâmica da procura (*Demand Response*), como uma forma de melhorar a eficiência da utilização da infraestrutura elétrica, possibilitando a prestação de serviços auxiliares utilizando recursos do lado da procura, ou seja, flexibilizando o uso das suas cargas, com o objetivo de alcançar um equilíbrio entre a procura e a oferta.

A *Demand Response* é vista como uma estratégia eficaz e confiável para o sucesso da integração de fontes de energia renováveis, numa perspetiva de gestão integrada dos recursos de energia, através da otimização e controlo do perfil de consumo do utilizador final, em tempo real, sempre que for solicitado pelo operador do sistema elétrico.

Um agregador de sistemas de gestão de energia, designado *Energy Box Agregator* - EBAg, foi concebido para funcionar como um intermediário entre o utilizador final e o operador da rede e / ou mercado de eletricidade, cujo objetivo é influenciar a procura de energia e oferecer serviços auxiliares através da implementação de uma estratégia de "*load follows supply*" num contexto de *Smart Grid*. O agregador tem a capacidade de utilizar a flexibilidade de consumo oferecida por cada utilizador final para satisfazer as exigências de serviços do sistema, diminuindo ou aumentando a potência pedida à rede durante um dado período de planeamento, contribuindo para garantir a estabilidade e o bom funcionamento do sistema elétrico.

Com este propósito, foi desenvolvido um modelo de otimização multiobjectivo para maximizar os lucros do agregador, tendo em conta as receitas do operador do sistema e / ou mercado de eletricidade e pagamentos ao utilizador final. O modelo considera ainda a maximização da equidade, minimizando as desigualdades entre os valores de flexibilidade de carga fornecida pelos utilizadores finais agregados em *clusters*. Uma abordagem híbrida baseada em Algoritmos Genéticos e algoritmos de Evolução Diferencial foi concebida para lidar com este modelo. Posteriormente, esta abordagem foi estendida para realizar uma análise de robustez das soluções obtidas.

Palavras-chave: Sistemas de gestão de energia elétrica, agregador, gestão da procura, Algoritmos Genéticos/Evolucionários, Evolução Diferencial, otimização multiobjectivo.

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List of Acronyms and Abbreviations

AS	Ancillary Services
CPP	Critical Peak Pricing
CPR	Critical Peak Rebate
DE	Differential Evolution
DER	Distributed Energy Resources
DM	Decision Maker
DR	Demand Response
DSO	Distribution System Operator
DSM	Demand Side Management
EA	Evolutionary Algorithm
EV	Electric Vehicle
EBAg	Energy Box Aggregator
EM	Energy Market
EMS	Energy Management System
EP	Evolutionary Programming
ES	Evolutionary Strategies
EU	European Union
GA	Genetic Algorithm
GHG	Greenhouse Gases
HEMS	Home Energy Management System
ICT	Information and Communication Technologies
IoT	Internet of Things
LEB	Local Energy Box
MOEA	Multiple Objective Evolutionary Algorithm
MOGA	Multiple Objective Genetic Algorithm
MOO	Multiple Objective Optimization
NPGA	Niched-Pareto Evolutionary Algorithm
NSGA	Non-dominated Sorting Genetic Algorithm
NSGA - II	Elitist Non-dominated Sorting Genetic Algorithm
PS	Power System
RES	Renewable Energy Sources
RTP	Real-time Pricing
SG	Smart Grids
SO	System Operator
SPEA	Strength Pareto Evolutionary Algorithm
SPEA 2	Strength Pareto Evolutionary Algorithm 2
TOU	Time-of-use
TSO	Transmission System Operator
VEGA	Vector Evaluated Genetic Algorithm
WBGA	Weight-based Evolutionary Algorithm

Part I

Energy Management Systems Aggregator: Review and EBAg concept

1. Chapter I - Introduction

1.1 Problem and Motivation

The efforts to reduce reduce greenhouse gas (GHG) emissions related to electricity generation as well as foreign dependence of fossil fuels have been leading to a fast increase of the deployment of generation based on renewable energy sources (RES), in particular photovoltaic and wind power [1]. RES are being deployed not only as bulk generation facilities but also as distributed local generation facilities or even private consumption infrastructures. However, the associated generation patterns normally do not follow the typical demand profile and cannot be neither predicted with great accuracy nor reliably dispatched. In fact, RES generally exhibit significant temporal variability due to environmental conditions, which are inherently inconstant and outside the control of generators and SO, often requiring the dispatch of reserve resources.

The DSO is responsible for distributing high/medium/low voltage power and delivery it to end-user costumer premises, and the TSO is responsible for the very high/high voltage infrastructure connecting generation plants and DSO's transformer stations. Since the operation duties of DSO and TSO responsibilities and roles can vary between countries, in this thesis we refer generically to an SO entity. The SO function may be owned by the TSO depending on the organization of the energy sector of each country. The SO has the responsibility to ensure the security and reliability of the power system, in real-time, and coordinate the supply and demand of electrical energy, avoiding oscillations in frequency or voltage and interruptions of supply. The SO is responsible to assure the quality of service and the security of supply.

The SO must dynamically provide AS, that is, the balancing services that are delivered by power system entities to the SO for ensuring reliable system operations, to assist matching demand and ensuring technical quality parameters, including frequency stability and voltage control [2]. According to Eureletric "it is not easy to define what AS actually are, and how they should be procured, anyone attempting to create rules for an AS market might soon see his structure rapidly becoming unmanageably complex" [3].

The penetration of RES represents a major challenge and technologies, management and control strategies, as well as intelligent systems based on optimization algorithms are essential to guarantee the system reliability and technical quality patterns. Presently, the adjustment is mainly done using “fast-reacting” generation technology systems (mainly as peak plants, based on fossil fuels) to safeguard the system against unexpected events such as production deficit, speedy generation variation or load variation [1]. Therefore, additional methods to compensate the unpredictable imbalances should be envisaged, including reduction of load during peak hours or periods of generation reduction, by interrupting, shifting or re-parameterizing end-use loads, possibly also using storage systems, such as batteries of EV that can, in the near future, be used in the Vehicle-to-Grid (V2G) mode. A better integration of intermittent sources needs to take into account these issues, namely concerning the possibilities of managing demand in a perspective of integrated energy resources management to deal with supply volatility.

The price of electricity usually encompasses the costs to build, finance, maintain, and operate the power plants and the whole network infrastructure. Wholesale electricity prices may change in short time frames. However, in general, end-users are subject to rates based on seasonal cost of electricity, without being affected by market conditions. Changes in electricity prices generally reflect variations in electricity demand, availability of different generation sources, fuel costs, and power plants. In a deregulated context, the SO should deal with the variability of electricity costs and the demand requests, in order to manage the whole system securely and safely [4].

The availability to modify the generation injection (generation flexibility) and/or load consumption profile (load flexibility) in response to a signal (a price signal or of other type) is an instrument to provide AS [5]. Generation flexibility can be provided by generators having large up and down ramping rates, and short minimum up and down time. The interconnection with more flexible systems is another conventional solution for the provision of AS, using the availability of neighbor regions/countries, although this involves that transmission lines capacity is kept for the reserve market, which will bound the capacity in the day-ahead spot market and thereby probably originate higher electricity prices. However, relying solely on generators to provide flexibility is expensive because it often involves producing energy with more agile but less efficient generation units or operating thermoelectric power plants below their maximum efficiency loading.

The electricity consumption in households has been steadily growing due to the widespread utilization of new types of loads and the requirement of higher levels of comfort and energy services, representing a significant untapped savings potential due to waste and load flexibility [6,7]. The distribution of electricity consumption in households has been characterized, and it has been shown that some loads display flexibility in their usage; consequently, if appropriately managed those loads can serve as demand side resource able to offer responsive energy behavior [6].

As an example, washing and drying appliances can be rescheduled to periods of lower energy consumption (lower prices) thus flattening the demand curve, or periods of higher energy generation from RES, therefore better matching consumption with RES generation. Thermal loads (cold appliances, water heating and air conditioning systems) can be interrupted during shorts periods of time without major reductions in service quality, to avoid the most unbalanced situations between generation and consumption, compensating the effects of the variability of RES availability.

In a SG context, a modernized power system extensively using ICT, intelligent devices and autonomous controllers, with advanced data management, two-way communication means are incorporated across the entire system, from generation to consumption at the end-user premises. The gradual implementation of SG is expected to improve overall efficiency, reliability and sustainability [8], enabling the end-user becoming a *prosumer* (that is , simultaneously producer and consumer) and dynamic time-differentiated electricity tariffs being the price structure seen by customers [9,10]

DR programs use price signals and incentive/reward/penalty schemes to influence changes in the end uses of electricity. In general, programs are designed to induce lower electricity consumption at times of high market prices or when grid reliability is endangered [11] as a way to manage power usage preferences to benefit not only end-users but also the whole system. To make DR programs operational, households need to have EMS based on fully interactive ICT, also making the most of the evolution of the Internet of Things (IoT) [1]. EMS are aimed at helping end-users optimizing energy usage, for instance, achieving energy savings and satisfying constraints on the quality of the energy service provided (namely concerning comfort requirements). However, in a scenario of low price signals from the grid, all EMS devices would attempt to achieve benefits for the end-user engaging in similar actions (for example, by shedding the same type of loads), eventually taking no notice of the instability that could impair the operation of the system, since the true impact of residential consumption arises when it is summed up over a large number of households. In this setting, DR can become a new source of revenue for entities that "aggregate" load flexibility and DR schemes. Energy

[1] The Internet of Things (IoT) id the interconnection of uniquely identifiable embedded computing devices within the existing Internet infrastructure. Typically, IoT is expected to offer advanced connectivity of devices, systems and services that goes beyond machine-to-machine communications (M2M) and covers a variety of protocols, domains and applications [322]. The interconnection of these embedded devices, including smart objects, is expected to usher in automation in nearly all fields, while also enabling advanced applications like a Smart Grid.

Management System Aggregators (EMSA) offer the opportunity to exploit the flexibility potential of small end-users and promoting their access to the retail electricity market by selling load flexibility and benefiting from rewards or lower energy bills.

By making the most of Smart Meters (SM) to provide real-time monitoring, technological solutions arising in the SG will be able to send signals to the end-user, namely price signals, enabling the optimal load management according to tariffs and users' preferences and quality of service requirements. These load management (LM) activities in the SG context can be viewed as additional DER to be taken into account in the integrated optimization of all energy resources. In the residential sector, where the size of individual LM resources is insignificant in comparison with the total demand, load aggregators and flexibility agents will expectedly play a crucial role by facilitating the integration of the demand side resource management into the global system operation.

Loads started to be faced as a possible solution to deal with security of supply problems in power systems after the oil embargo in 1973. At this time, DSM[2] was considered interesting from a technical point of view and made economic sense due to the momentary increase of the energy prices. Simple measures to incentivize efficiency in consumption and promote waste reduction were implemented by the electric utilities. The first phase of DSM was born under the form of energy conservation [12]. Later, DSM was defined in relation to Energy Efficiency, DR and Energy Conservation [13].

The evolution of planning procedures used by utilities in the late 1980s included all activities targeting the alteration of the end-user demand profile, in time and/or shape, to facilitate matching the supply including contributing to the efficient incorporation of RES [14], and also yielding significant savings both in generation and transmission [14,15]. DSM can be used as a tool to accomplish different load shaping objectives, such as peak clipping, valley filling, load shifting, strategic conservation, strategic load growth and flexible load shape, in a long-time horizon, as can be seen in Figure 1.

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[2] The term demand-side load management was introduced by Clark W. Gellings, in an article for IEEE's Spectrum in 1981. Shortly after the publication of this article, at a meeting of The Edison Electric Institute (EEI) Customer Service and Marketing Executives in 1982, Gellings altered the term to demand-side planning. This change was made to reflect the broader objectives of the planning process. Gellings also coined the term demand-side management and continued to popularize the term throughout a series of more than 100 articles since that time, including the five volume set Demand-Side Management that is widely recognized as a definitive and practical source of information on the demand-side management process [323].

Currently, one of the main DSM techniques to achieve a more flexible load shape is named DR, which, in general, needs to be executed in a short time horizon, that is, temporary, short-term changes. DR is a process to encourage and influence behavior changes in the end-user consumption patterns in response to incentives, such as price signals. According to the US Department of Energy [11], DR is defined as "a tariff or program established to motivate changes in electric use by end-use customers, in response to changes in the price of electricity over time, or to give incentive payments designed to induce lower electricity use at times of high market prices of electricity over time, or to give incentive payments designed to induce lower electricity use at times of high market prices or when grid reliability is jeopardized". In recent years, DR has progressed into a more dynamic resource that can contribute to price moderation and provide AS to utilities and SO [16].

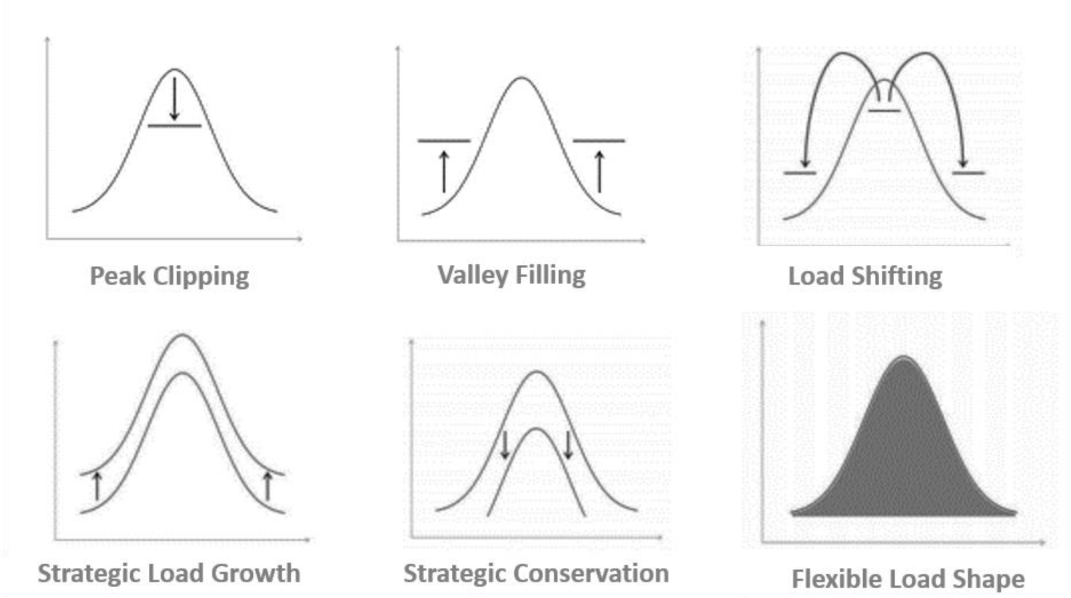

Figure 1 – Demand Side Management techniques, adapted from [17]

Inasmuch as security of supply is a concern, the major serious complications on account of power intermittence happen in peak load periods, when most system resources are being used and an abrupt power generation reduction/increase can cause serious consequences on the system reliability compromising the quality of services and security of supply. So, instead of acting on the supply side, DR programs and technologies have the potential to contribute to optimize consumption and reduce peak loads, avoiding peaks in the load diagram, as well as empowering the potential participation of end-users in the grid management [6].

A few recent studies have addressed the combination of demand and supply sides to implement DR programs for the provision of AS using load flexibility [18]. These services have been usually arranged by generators prepared to adjust their output quickly in response to unexpected imbalances between load and supply. The provision of these services by aggregating end-users load flexibility using DR programs is becoming an attractive alternative to the ones that involve the supply side [18].

This role can be performed by an aggregator energy management system (Energy Box Aggregator - EBAg), which is an intelligent decision-making mediator between the end-user (local energy box - LEB) and the grid (SO/EM) allowing the coordination of a large-scale dissemination of in-house DR devices (Figure 2). The EBAg is aimed at using the demand-side flexibility provided by clusters of end-users to provide system service requirements, involving lowering or increasing the power requested in each time slot of a planning horizon. This contributes to balance load and supply, avoiding peaks in the load diagram and coping with the intermittency of renewable sources, therefore increasing the overall grid efficiency by offering an attractive alternative to supply side investments on peak and reserve generation [19].

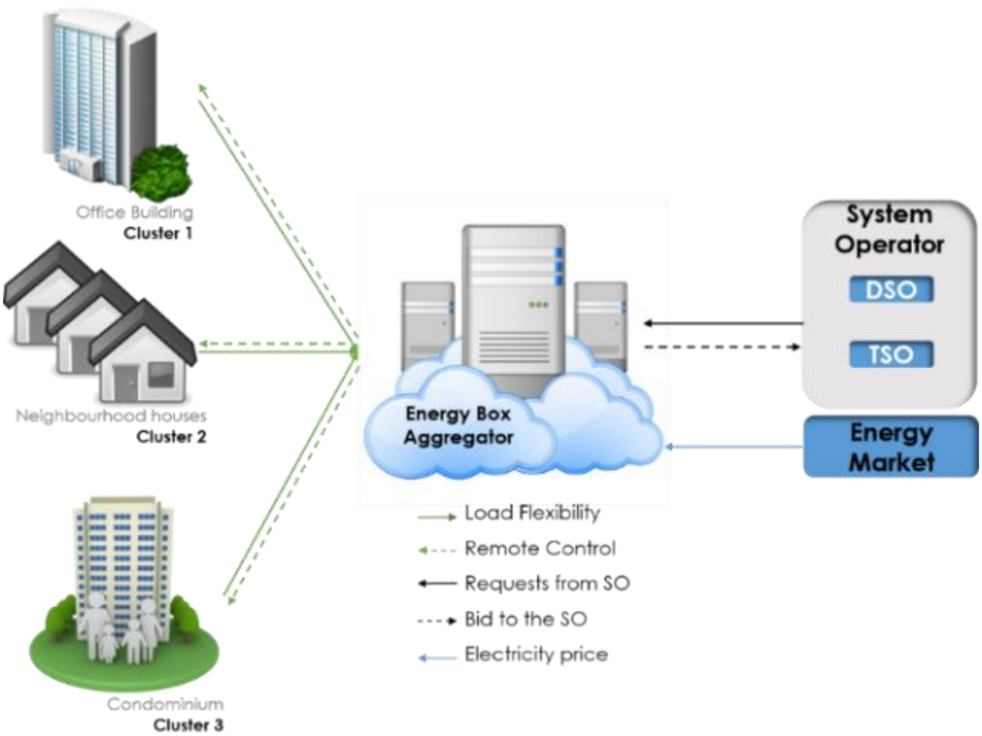

Figure 2 - EBAg global architecture

1.2 EU Policy Analysis

The Energy Efficiency Directive (2012/27/EU) requires DR to participate in the EM to provide balancing and AS to the system. This is possible using the EBAg as an intermediate entity between customers and the utilities/retailers. The Agency for the Cooperation of Energy Regulators (ACER) published a recommendation (no. 03/2018) [20] in July 2015 proposing that the origin of balancing energy can be power generation or demand facilities, instead of being only from generation capacity. This balancing energy is a reserve capacity that an aggregator, named a Balance Service Provider (BSP), has to agree to hold, submitting the corresponding bids of balancing energy to the SO. The ACER draws attention to the fact that the DR provider may confront significant entry obstacles into the "balancing service market" and adversities in the competition with the energy suppliers. To mitigate these barriers, the Agency proposes that actions should be done with the intervention of the Member States and National Regulatory Authorities (NRA) by *"implementing adequate measures to mitigate entry barriers and ensure demand-side response can compete at a level playing field or by enabling the provision of demand-side response independently of energy suppliers"*.

In this way, the ACER has established standards and common requirements that allow the implementation of DR independently of the energy suppliers, believing that this will facilitate the participation of DR entities in the balancing market. Those requirement are: "*(a) The provision that a BSP can provide the demand-side response service from a demand facility without the need for consent or a contract with the energy supplier of that demand facility or its Balance Responsible Parties (BRP); (b) The requirement that BSPs providing demand-side response independently of energy suppliers should be balance responsible; (c) The requirements for TSOs to adjust the final position and determine the allocated volume for the BRP of the BSP and for the BRP of the energy supplier; and (d) The requirement for TSOs to establish the financial settlement between the BRP of the BSP and BRP of the energy supplier."* This will require adjustments to today's balancing market rules, and the integration of the aggregator seems a promising direction for this purpose.

The concept of aggregator has also received special attention from the European Commission (EC) that perceives the aggregator as serving different power system entities (i.e. utilities, DSO, Independent System Operator / TSO / Regional Transmission Organization, Energy Exchange, Capacity Market and Energy Service Companies - ESCO) able to manage demand flexibility, such as load shedding and better load profiling [21–24].

In January 2015, the SG Task force published the report "*Regulatory Recommendations for the Deployment of Flexibility*" [25], where aggregators, as legal entities, are considered an essential means for the end-user to act in the market since they have the ability to extract the value of flexibility services on behalf of their customers.

The European Technology Platform on Smart Grid (ETP SG) initiative has aimed to provide strategic advice to the EC on the medium and long-term technological research and development needs in the area of SG, which can be seen in the ETP SG Strategic Research Agenda 2035 (SRA 2013). The aim is to intelligently integrate all connected users (including end-users) to efficiently deliver sustainable, economic and secure electricity supply [26,27]. There is an increasing interest in the wider implementation of DR opportunities across smaller commercial and residential groups, using intermediate entities such as aggregators. This is also due to technological developments in low-cost power electronics and ICT along with general growing recognition of the importance of customer behavior [28].

European countries are progressing towards the development of SG for the establishment of an efficient market for trading flexibility in electricity consumption and production [1]. The concept is based on a wholesale model, which determines the future roles of actors in the EM [2]. One main challenge of Horizon 2020, the EU Framework Programme for Research and Innovation, is the Energy challenge, which was designed to support the transition of the current power system to a reliable, sustainable and competitive energy system. The Energy Challenge is structured around seven specific objectives and research areas: Reducing energy consumption and carbon footprint; Low-cost and low-carbon electricity supply; Alternative fuels and mobile energy sources; A single, smart European electricity grid; New knowledge and technologies; Robust decision making and public engagement; Market uptake of energy and ICT innovation, with a budget of €5 931 million to support research projects between 2014 and 2020. One of the main priorities is "*Secure, Clean and Efficient Energy*", included in the section of Societal Challenges [29], which is focused essentially on the main pillars: Energy efficiency (the EU aims to progressively decrease energy consumption); Low Carbon Technologies (the EU aims to invest in the development of cost-effective and resource efficient technologies solutions to decarbonize the energy systems in a sustainable way). The research activities within this area cover RES and mechanisms for ensuring the better integration of RES in the power system, in which Aggregators, Smart Cities & Communities play a role (the EU will invest in research and development of advanced technological solutions and services allowing the involvement of end-user and communities in the creation of Smart Cities, namely for the areas of Energy, Transport and ICT). As a policy driver, the EU wants a revision of the Strategic Energy Technology Plan –SET Plan [30], in order to better respond to new challenges and consolidate research and innovation in the energy area across Europe. As can be seen on the Work Programme 2018-2020 [29], cf. section of "*Secure, Clean and Efficiency Energy*" of the Energy Efficiency Call 2018-2020, specifically on EE-23-2017: Innovative financing schemes ("*schemes based on project* *aggregators or clearing houses at regional or national level, which should support project development and match demand and supply of energy efficiency finance*"). Also in the Low-Carbon Energy, specifically on LCE-04-2017: Demonstration of smart transmission grid, storage and system integration technologies with increasing share of renewables ("*New approaches to the wholesale market facilitating the participation of variable renewable energy sources, remunerating adequately new flexibility services to the grid such as offered by storage, active participation of demand and new players such as aggregators and reducing the cost of operations*"). At the same time, in 2015, some reports have been solicited by the EC to their advisers regarding aggregators [25,31,32], which reveals the need to take into account this new and emerging middleware entity in the power system, namely concerning its ability to contribute to the successful penetration of RES. In [32] the aggregator is mentioned as a crucial entity to gather the flexibility from many small sources and facilitate active participation of DER. The exploitation of the aggregator concept will be a stimulus for the competitiveness, innovation and development of new services and solutions. The aggregator role can be carried out by diverse present players or be an independent entity.

Therefore, as can be seen in several policy publications, the role of aggregators, as entities implementing DR to provide AS to SO is an emerging topic, with impact on the entire chain of the energy industries.

1.3 Objectives of the Research and Contributions

The main objective of the PhD research was to develop the concept of EBAg and its optimization models, capable to contribute to the implementation of "load follows supply" strategies to increase grid efficiency, ensuring the required level of supply security, reliability and quality of service, considering end-user flexibility of demand side resources and both grid and load technical constraints.

The main results of the research were:

- Development of the EBAg concept;
- Development of a multi-objective optimization models for the EBAg;
- Development and implementation of algorithmic approaches based on evolutionary computation to obtain solutions, including robustness assessment;

The methodological approach to address the problem is based on an EA coupled with a differential evolution (DE) algorithm to deal with a multi-objective optimization (MOO) model. This model considers the maximization of the EBAg profit and the minimization of the inequity among end-user clusters, by means of the maximum relative difference between the load flexibility provided by the cluster and the one used by the EBAg, as a surrogate for fairness in the usage of end-user load flexibility.

The research questions framing the research carried out were:

R.Q.1 - What are the main operational features that an EBAg should have to optimize energy consumption using load flexibility along with supply options?
R.Q.2 - What should be the customer loyalty business model, that is, what kind of end-user engagement should be done, including financial and non-financial incentives, to promote DR activities from the EBAg?
R.Q.3 - How to ensure the efficient use of the electric power system by using the services offered by the EBAg, such as ancillary services?
R.Q.4 - What should be the load follows supply strategy in the SG context using the EBAg?

The main contributions of this dissertation are presented in the three parts of this thesis:

1. Part I – Energy Management Systems Aggregator: Review and EBAg new concept:
   A comprehensive literature review has been done regarding the categorization and roles of AS (which are not defined in a uniform way in different countries), as well as the impacts of the penetration of high shares of RES in the power system. Also, a review of the DR programs and models has been done, as well as regarding current DR implementations. Experiences of aggregators have also been reviewed, which has revealed particularly challenging since this is a recent topic in the SG context, and there is no uniform concept in the literature.
2. Part II - Energy Box Aggregator Model and Algorithms
   The main contribution of this part of the thesis consists in the EBAg multi-objective model description, the hybrid algorithm implementation making the most of the features of EA and DE, and the results obtained for a case study based on real data gathered during one year using the Cloogy® technology [33].
3. Part III - Robustness Analysis of Non-dominated Solutions
   Development of a methodology to analyze the robustness of the non-dominated solutions obtained using the EBAg model and the hybrid EA implemented. A critical analysis of the work developed in this thesis is presented, along with future work proposals.

1.4 Outline of the Thesis

This thesis is divided in three parts, composed by chapters comprising a specific aspect of the EBAg proposed.

Part I: Energy Management Systems Aggregator: Review and EBAg concept:

Chapter 1 – Introduction: In this chapter context information is offered, exposing the problem to be addressed, the motivation, the objectives and the main contributions of the research developed.

Chapter 2 – State-of-the-Art: A comprehensive literature review is presented, with the aim to give the essential background and definition of key concepts required for the following chapters regarding to AS, DR and Energy Management Systems Aggregators.

Part II: Energy Box Aggregator Model and Algorithms:

Chapter 3 – MOO Problems: This chapter introduces the basic concept and approaches of MOO. The presentation of algorithms is focused on EA and DE, which were utilized to create the hybrid algorithmic approach implemented.

Chapter 4 – A Multi-Objective Model for the energy Management System Aggregator: In this chapter, the MOO model for the EBAg is presented with the case study, as well as a brief overview of the business model using the Canvas methodology.

Chapter 5 – EBAg Algorithm Implementation, Results and Discussion: In this chapter, the algorithmic approach is described as well as some illustrative results.

Part III: Energy Box Aggregator – Robustness analysis of Non-dominated Solutions:

Chapter 6 - Uncertainty and robustness in optimization: This chapter presents the background information and main concepts regarding uncertainty and robustness. A short literature review is presented regarding approaches to perform robustness analysis in MOO problems. The developed methodology and the results of the analysis of robustness of selected non-dominated solutions are also presented.

Chapter 7 – Final Conclusions and Future Work: In this chapter the main conclusions of the research work are presented and possible future research directions are discussed.

2. CHAPTER 2 – A REVIEW OF THE STATE-OF-THE-ART[3]

This section focuses on the role of energy management systems aggregators (EBAg), concerning actual practice in industry as well as research, which can be seen as relevant players contributing to that endeavor. A review of recent literature and projects is made, putting in perspective the role of EBAg in the SG context, in association with DR programs and technologies, involving the participation of end-users in the provision of AS. The aim is to recognize recent trends, opportunities, challenges and potential barriers regarding the creation of an EBAg to improve the overall system performance, characterizing the services provided by aggregators and identifying potential research gaps.

2.1 A REVIEW OF ANCILLARY SERVICES

Historically, the electric utilities were vertically integrated, owning and operating the whole electricity industry chain from generation to transmission, distribution and supply. Therefore, AS were required and provided within the same company. With deregulation and liberalization, those activities of the electric utilities have been separated, in general becoming independent legal entities with independent ownerships. This creates additional difficulties in the definition and procurement of AS. The creation of rules for AS markets may lead to complex structures, which are difficult to manage. In this thesis, we will adopt the definition of AS of Eurelectric, the Association of the Union of the Electricity Industry, which published a detailed analysis on the characterization of AS in different European countries [3,5].

AS are services needed by the transmission and/or distribution SO to enable maintaining the integrity and stability of the network infrastructure as well as power quality, reliability and security on an economic basis. These needs can be fulfilled by connected generators, controllable loads and/or network devices to assist the SO maintaining the frequency and voltage between the required boundaries and recuperate the system in case of perturbation or failure [3,11,34]. These balancing needs are increasing due to the penetration of RES, in order to deal with its inherent variability and

[3] This chapter is partially based on Andreia M. Carreiro, Humberto M. Jorge, Carlos Henggeler Antunes, Energy management systems aggregators: A literature survey, Renewable and Sustainable Energy Reviews, Volume 73, 1160-1172, 2017. http://dx.doi.org/10.1016/j.rser.2017.01.179.

uncertainty. The next section presents the different AS categories, focusing on the most prominent to be satisfied with the utilization of an EBAg based on DR.

2.1.1 Ancillary Services categories

The literature offers different definitions and characterization of AS. In [35], AS are separated into three groups: Interconnection services, which are linked to the frequency response services between diverse areas; Generation/Demand balancing services, which involve regulation responses, load following and contingency reserve; and Local Services, which include voltage and reactive power control to support the active power transmission. In a classification based on the system needs in terms of operating requirements, AS can be broadly divided in four main categories that are essential to maintain the system operation stability: stability control, voltage control, restarting system and frequency (Figure 3).

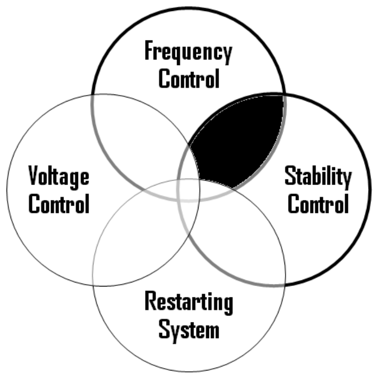

Figure 3 - Types of AS. Area filled with black is where the EBAg may have a major contribution (adapted from [3])

The first three types of AS are not suitable to be provided by load flexibility, but it can play a role in frequency control.

Stability Control is a service aimed at compensating the transmission system faults through emergency control actions using special equipment such as dynamic braking resistors or power system stabilizers to maintain a safe transmission system [36].

Voltage Control is a service essential for maintaining voltage in the power system within the recommended boundaries during regular operation and disturbances, guaranteeing the balance of injection and absorption of reactive power. Voltage control can be delivered by dynamic sources, such as generators, synchronous compensators and static resources [37].

Restarting System consists in a restoration capability of a generation unit to start up without external power supply service when large blackouts happen. The most common is the black start capability.

Frequency Control (FC) helps the system to maintain the frequency within the allowed margins by continuous modulation of power using the operational reserves. It includes automatic (primary and/or secondary) and manual (tertiary) frequency regulation. This service is mainly provided by generators but can also be provided by flexible loads and storage units. The primary response corresponds to the automatic response to frequency changes with a capability of time response of seconds, while the secondary response is the automatic response to frequency changes that takes over from the primary response and partially recovered system frequency.

Reserve services are of three types:

i. **Spinning reserve (SP):** this service consists in increasing or reducing power generation and/or reducing load at short notice, being performed by partially loaded generation units and interruptible end-users. Spinning reserve can start quickly and be available in 10 minutes. The use of flexible load to provide SP allows for the reduction of reserve costs. Moreover, it prevents situations when the SO needs to appeal for rolling blackouts in order to avoid blackouts of the whole system.

ii. **Standing reserve (ST):** this is an offline service that in some special cases can be brought online quickly to meet additional contingencies. It can be fully available within 30 minutes and may act as a backup for the SP.

iii. **Remote automatic generation control (RG):** this service consists in regulating frequency by controlling the output through a centrally based control system. It may mean operating the Secondary Response but also controlling a whole plant. This is a control capability to regulate the power system frequency through a centralized control system far from the network.

A certain amount of active power, usually called system reserve, is kept available to perform frequency control - when the system frequency tends to decrease it is necessary to inject more active power or reduce load (positive reserve), while when the frequency tends to rise it is necessary to reduce active power generated or increase load (negative reserve) [38,39]. Reserve services can be provided by an EBAg and may be divided in three categories: Primary reserve, secondary reserve and tertiary reserve, as displayed in Figure 4.

The **primary reserve** is requested by a local automatic control that adjusts the active power generation and the consumption of controllable loads to restore rapidly (in less than one minute) the balance between load and supply. The demand side may also contribute to this control through the auto-regulation of some frequency sensitive loads [40].

The **secondary reserve** is a centralized automatic control that regulates the active power produced in generation units to reestablish the standard value of frequency. That is, while primary control stops the frequency fluctuations, secondary control reestablishes the frequency target value and should be able to act in less than ten minutes.

The **tertiary frequency** control response consists in manual changes in the generation unit and is used to reestablish the primary and secondary reserve at previous levels before the frequency fluctuation.

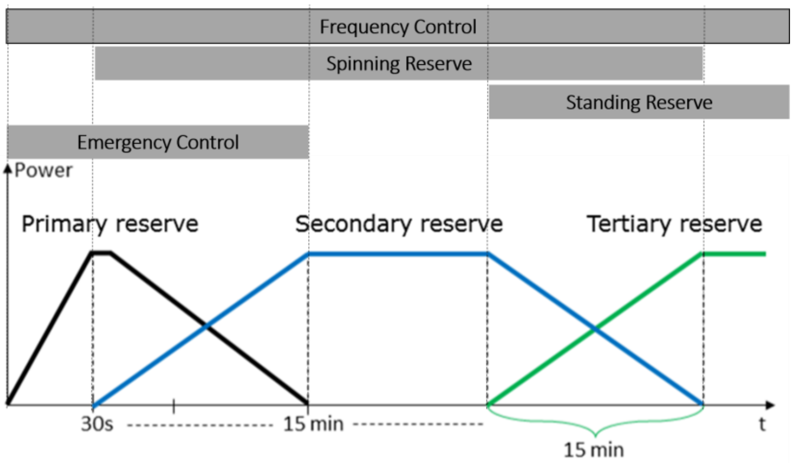

Figure 4 – Frequency control reserve characterization (quick – less than 30 seconds; medium – around 10 minutes; slow – around 30 minutes)

2.2 AS PROVIDED BY DR STRATEGIES

The main objective of the application of a DR program may be summarized as follows:

- Reduction of the total power consumption, so that mutual profit for the power utility and the end-users is achieved. This reduction should occur not only in the end-user demand, but also in transmission and distribution system losses [41];
- Reduction of the total power generation, which is the main result of the aforementioned objective. Under the successful implementation of a DR scheme, the need of activating more expensive power plants and build new ones to meet peak demands is mitigated [11];
- Change of the demand pattern, optimizing the end-user consumption, to follow the available supply creating a “load follows supply” strategy, especially in regions with high penetration of RES, to maximize the overall reliability being environmental friendly [18,42];

- Reduction or even elimination of overloads in the distribution system.

A DR scheme must consider security mechanisms for the protection of privacy associated with energy usage information that is acquired by smart meters or local EMS for the DR provision [43]. Moreover, a DR scheme must be designed to engage end-users to take part in the program, through the delivery of incentives to change their load consumption patterns without jeopardizing comfort [44].

The adjustment of the usage of electrical energy by end-users is made as a response to changes in electricity prices over time, contractual agreements or when system reliability is threatened. This adjustment is executed through the cooperation of three main participants [45], as illustrated in Figure 5:

1. End-users (residential, commercial or industrial) loads that take part in the DR program;
2. A DR Aggregator that is connected to the end-user's EMS and executes the DR programs;
3. A SO that manages the system.

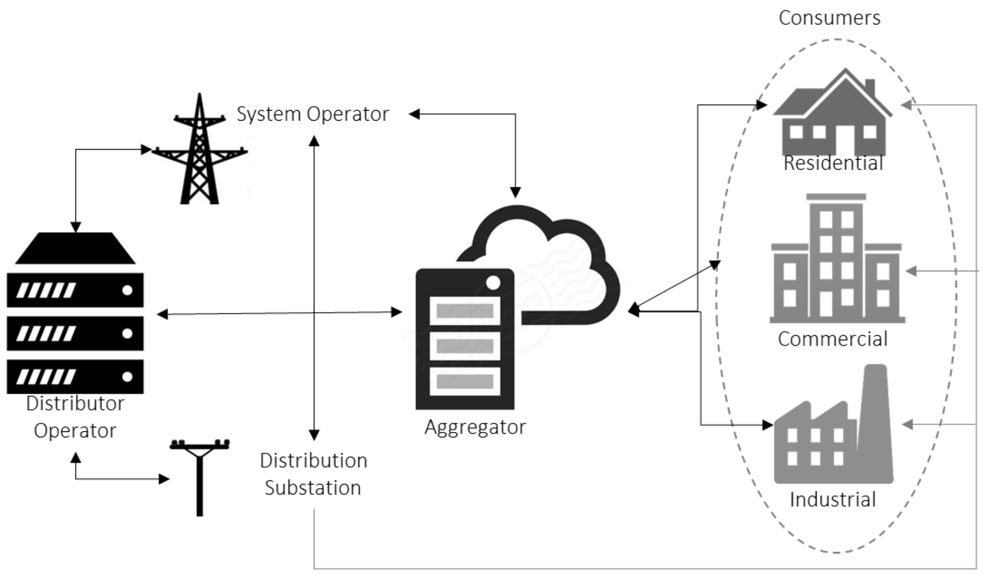

Figure 5 - Main participants in DR Programs, adapted from [46]

In general, the process of a DR scheme begins at the SO, which determines the demand volume that should be reduced or increased in a certain period. This information is submitted to the DR Aggregator, which then selects the participating end-users based on their availability. Taking into account the number of end-users that agree with the proposed DR scheme, the EBAg calculates the total load flexibility that can be offered in reply to the SO request, the amount of flexibility to be used from each participant end-user, and reports back to the SO.

Examples of case studies performing the role of a DR Aggregator are described below.

Taking into consideration the development of the electricity mix of Flores Island (Azores), which includes a high integration of RES, the impact of DSM strategies is evaluated in [47]. The electricity mix was modeled using TIMES - The Integrated Markal-Efom System to optimize the investment and operation of wind and hydro power plants until 2020 taking into account situations of consumption increase, development of technologies allowing the implementation of DR programs in the residential sector, and campaigns of promotion of efficient behaviors to remove standby power. The authors concluded that DR strategies eliminate the need of ongoing investments on new generation sources from RES; load shifting strategies should be used to help increasing the capacity factor of the existing generators and further postpone the investments to build new plants [47].

A DR algorithm to regulate frequency (± 0.05Hz of 60Hz) using responsive loads whereas reducing the quantity of load changes after disturbances was developed in [48]. A dynamic model for an isolated micro grid and an upgraded adaptive hill-climbing approach were developed to deal with the problem. The simulation model consists of an incremental control strategy to minimize the amount of responsive loads manipulated. As a result, quality-of-service (QoS) for customers is ensured, while a significant amount of responsive loads is accessible for extra control to answer to unforeseen system instabilities.

A framework for dealing with the discomfort caused to the end-users and the incentives required to accomplish DR benefits is considered in [49], based on a model of residential energy consumption. A management methodology appropriate for most residential technologies and objectives for a single house is presented in [50]. The simulation of different scenarios shows that the objectives of single and multiple houses can be reached [50,51]. The problem of finding the best solution is modeled as an Integer Linear Programming (ILP) model to minimize cost while matching all heat and electricity demand considering multiple time intervals. A heuristic for solving the model was developed making it possible to implement the application in an embedded energy efficiency controller. Since the cost function defines the interaction between devices, cost functions must be adapted for every configuration and usage scenario.

A number of technologies can provide flexibility in the usage of energy, involving end-user loads and energy storage. However, only large end-users, for example, industrial clients, are presently able to sell their load flexibility on an individual basis and participate in the EM. In addition, many manufacturing processes have critical temporal dependencies, which must be scheduled with precision. Small (residential and commercial) end-users face high barriers in accessing the EM. The design of effective DR programs for these clients is far more complicated compared to industrial end-users, mainly due to their diversified consumption patterns and need to guarantee an ample end-user acceptance [23].

A communication infrastructure that provides connectivity among systems, devices and applications is essential for the effective and reliable operation of the SG [52]. The general communication requirements for the implementation of a DR program refer to the provision of a two-way information flow between the entities that participate in the program. Other requirements are necessary for the implementation of a DR program [53]:

i. Quality of Service: The provision of QoS guarantees for the communication technologies is essential for the smooth implementation of a DR program. The bidirectional networking of the SG should ensure that control and command, emergency response and pricing signals are reliably transferred without being affected by the number of the end-users connected. For real-time sensing and metering purposes, which are used in various pricing schemes, latency values of a few milliseconds should be achieved [54].
ii. Interoperability: The cooperation of different systems is vital to data exchange between the components of the SG. To provide interoperability and seamless data exchange between interconnected elements of the SG, the adoption of open standards across the communication infrastructure is an essential operational issue [55,56].
iii. Scalability and Flexibility: DR becomes more effective when a large number of end-users is engaged in programs, since further manageable loads are accessible [57]. Thus, a highly scalable communication infrastructure is essential for the accommodation of a large number of devices and services, through the evolutionary implementation of the infrastructure on a broader scale [54]. Cloud based architectures for DR implementation can be considered as an effective solution that leverages data-centric scalable and flexible communication between the utility and the end-users [58].
iv. Security: Network security is an important factor in the operation of SG, since it provides the means to maintain data integrity, confidentiality and authentication, while it facilitates non-repudiation [59]. Several security issues may compromise the effectiveness of a DR scheme. Tampering of information of a pricing program may trigger financial and legal problems, while malware may cause a severe damage to the power system [60]. It is therefore essential to implement secure DR programs that protect the private data of end-users, prevent unapproved access that attempt to delay, block or even corrupt information transmission,

and provide authentication, authorization, auditability and trust components to the communication infrastructure [61].

More comprehensive studies on the communication requirements, challenges and solutions for DR, are presented in [53,54,60–63]

2.2.1 Demand Response Programs

DR programs can be enhanced using motivation schemes that are offered to the end-users for their efforts to reduce, shift, shed, reparameterize, or interrupt their load operation. Two main approaches may be distinguished in the scope of the aggregation of demand-side resources and their corresponding capabilities in the provision of AS presented in the above section.

DR programs may be divided into two main approaches, namely Incentive Based Model (IBM) and Price Based Model (PBM) (Figure 6 [64–66]).

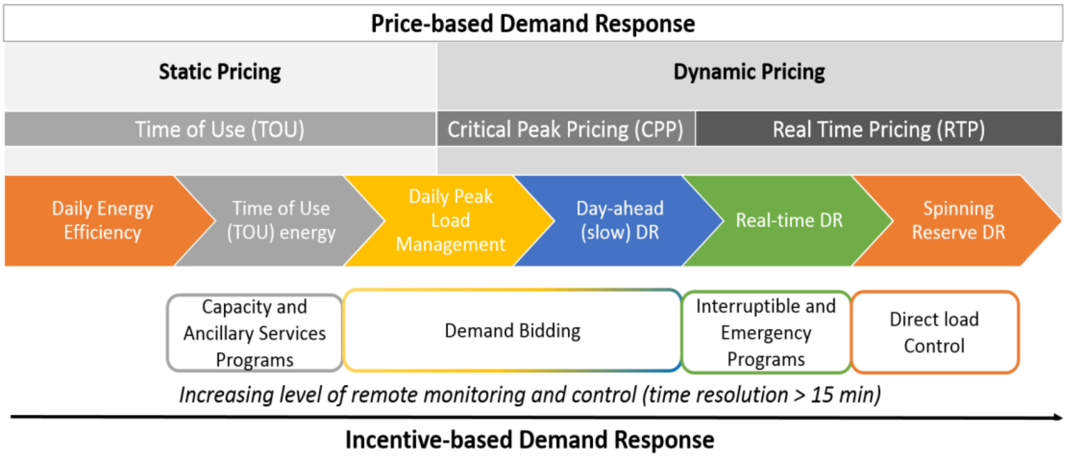

Figure 6 - Types of DR Programs

2.2.1.1 Incentive-based Model

IBM include programs that offer fixed or time-varying incentives (payments) to end-users to reduce their electricity usage during periods of system stress as required by the SO [67]. Customer enrolment and response are voluntary, but in some cases the end-users are under specific contract constraints and can be penalized when failing the contractual response.

IBM programs can be further categorized into classical programs and market-based programs, and they can be offered at both retail and wholesale market [68]. End-users participating in classical programs obtain participation payments, usually as bill credits or discount rates. In market-based programs, end-users are rewarded for their performance, depending on the amount of reduction of electricity usage during critical conditions, such as frequency and voltage instabilities, transmission line congestions and management of operations.

IBM are more focused on industry and commercial sectors where the contracts are established between the electricity end-user and the service providers, which may be the SO, utilities, the EBAg, other third parties, etc. [69]. IBM may be divided into four broad categories, as presented below.

2.2.1.1.1 Classical Programs

Direct Load Control (DLC) enables the power utility to remotely cycle or turn off end-use electrical equipment, controlling directly the appliances with a (previously known) participation fee compensation [15,70]. These appliances are typically thermostatic loads such as air-conditioners, water heaters, etc. The load control is feasible through the installation of switches at the customer premises that communicate with the utility. In some cases, control signals can also be sent to the customer to influence control actions. DLC programs are mainly offered to residential or small commercial end-users and they can be normally deployed within a relatively short notice [71]. End-users that participate in a DLC program obtain financial incentive to decrease their energy consumption under predefined thresholds.

Interruptible/Curtailment (I/C): The end-user is in control of appliances, making a commitment to modify the load upon receiving a request, for example, for curtailing the total consumption to a predefined level. If the end-user responds positively, he will receive a bill discount or credit in exchange for agreeing to reduce the load during the system request and contingencies. If the end-user does not curtail, he can be penalized according to the contract terms and conditions [72,73]. In general, end-users must respond within 30 to 60 minutes after being notified by the utility, while the total amount of time that a utility can call for interruption is capped [74].

2.2.1.1.2 Market-based Programs

The Emergency Demand Response (EDR) is called whenever the system security is in danger. EDR is a kind of market-based program, but can also be a combination of DLC and I/C programs, since they provide incentive payments to end-users for reducing their power consumption during reliability triggered events [75]. End-users can choose not to curtail and therefore disregard the payments, which are usually specified beforehand. End-users get incentive payments for helping to resolve system stability during security events.

Demand Bidding (DB), also known as *negawatt* program, is typically useful for large consumers, who offer load flexibly capacity bids in the EM [75]. The end-user is obliged to reduce the load by the quantity specified in the bid [71,76].

Capacity Markets (CM) is a market-based program offered to end-users who are able to provide predefined load flexibility/reductions as AS to replace conventional generation units [11,77]. The end-user commits to provide load reductions when system contingencies arise, receiving an up-front payment for offering the load flexibility plus a payment for the availability of the load flexibility to be used in case of an event [78]. Participants are obliged to demonstrate that a minimum load curtailment is achievable, while they receive guaranteed payments even if they are not called to curtail.

The **Ancillary Service Market (ASM)** is a program in which the end-user bids load reduction/curtailment commitment in the spot market, as operating reserves. Prices can be dynamic with hourly or faster variations according to system conditions. If the bids are accepted, participating end-users are paid the market price for committing to be on standby. Once the load reduction is requested and used, the participants are notified by the SO and they are paid for the energy provided [11,74,79].

2.2.1.2 *Price-based Model*

In PBM (also known as price-based DR) end-users are granted time-varying prices that are defined based on the electricity cost in different time periods. PBM has been triggered by the rise of deregulated EMs using price signals. Large industrial clients were interested to reduce their consumption during high-price periods and retailers encouraged their residential clients to flatten out their consumption profile using static and dynamic tariff structures [80]. Three categories of PBM may be identified, which are briefly referred to below.

2.2.1.2.1 Static Pricing

Time-of-Use pricing (TOU) divides the day into time blocks with different electricity prices, which may be hours within a day or days within a week. These prices are fixed for a specific period, being higher at peak hours and cheaper in off-peak hours, with the aim to incentivize the end-user to reduce the consumption in peaks hours and increase the consumption in off-peaks hours in order to allow a more efficient use of the generation, transmission and distribution resources [81,82]. TOU tariffs are also used as encouragements in household simulation models that produce representative load profiles [83]. The effectiveness of this scheme depends on attractive off-peak prices and relatively high prices in peak-demand hours [84]. A study showed that TOU programs offer the smallest reduction in the peak demand among all programs reviewed [85].

2.2.1.2.2 Dynamic Pricing

Real Time Pricing (RTP) typically reflects hourly wholesale prices and requires a strong involvement from the end-user. Under an RTP scheme, the electricity provider announces prices on a rolling basis. These prices are determined and announced before the start of each time period full implementation. In general, end-users receive new hourly electricity prices between a day-ahead and an hour ahead. This pricing scheme allows reflecting the underlying cost of energy at all times [86]. To be broadly disseminated in the residential market, an RTP scheme should rely on the two-way communication capabilities of the SG, which together with an EMS installed at the customer's premises will make decisions regarding consumption, and possibly microgeneration and storage [87].

Critical Peak Pricing (CPP) adds a critical peak component to TOU tariffs. This additional component is only applied during critical peak hours/events for a limited number of hours per year where energy prices change due to system stress/critical conditions [88,89]. The participant end-users receive notification of the new energy price usually a day-ahead. The ratio of on-peak to off-peak price is higher on CPP events than in TOU programs [90]. From the energy provider point of view, significant load reduction during critical periods can be achieved under this pricing scheme [91], but with high probability of negative net benefits [92]. For this reason, this tariff is more frequently applied to large commercial and industrial consumers where the baseline profile is more constant.

However, the end-user engagement does not rely on price signals only. As a key factor for the success of these programs, new technological devices have emerged in the market allowing residential end-users to follow the household consumption in real time [69].

2.2.2 Demand Response models

The EBAg can play the role of an intermediary entity in the implementation of DR programs. There has been an increasing trend of research works in the last two decades dealing with DR issues namely within the evolution to SG [73]. This research effort is briefly reviewed below, presenting their key characteristics and making a critical analysis.

In [93], various DR models that are applicable to wholesale and retail EM are presented, in which existing DR models are classified according to the nature of participants and market conditions.

Reliability- and price-based DR programs are analyzed in [94], concluding that it is less beneficial if both programs are implemented independently. In order to accomplish higher benefits, a hybrid model is proposed in which both programs are synchronized using an information management system [94]. DR strategies, such as load shifting and peak shaving, have been taken into consideration in the implementation of a household load control model presenting properties of both centralized and decentralized control methods [95]. The reliability of the centralized method matches the controllability and predictability of the decentralized method to give best performance (appraised based on predictability and delay). Household parameters are changed in accordance with the end-user priorities and requirements.

An EMS system for automatic DR is proposed in [96] to reduce the peak load in households taking into account the end-user's requirements and comfort level. The HEM system uses the Zigbee communication protocol and allows end-users to regulate the consumption of the smart devices (air conditioners, clothes dryers, water heaters and EVs) in response to the signal received from the energy service provider. The smart devices are monitored and controlled using an embedded microcontroller to measure voltage, current and load factor, and communication modules [97].

Several ongoing and concluded projects around the world based on DR programs are reviewed in [98] offering an overview of the scope and results of actual field tests with residential end-users, which will be presented in the next section.

2.2.3 Pilots of Demand Response Programs

The first experiments with dynamic pricing approaches for residential end-users were carried out in the 1970 decade, sponsored and promoted by the U.S. Federal Energy Administration, where the main objective was to evaluate the end-user response, that is, the DR subject to different price stimuli. After 1990 some pilot studies were carried out, in a non-controllable environment, to analyse the end-user response subject to dynamic (time varying) price rates to analyse the impact of DR programs in the reduction of consumption in peak periods. The summary of these results is presented in Table 1 ([99]).

Table 1 – Pilot of DR programs for loads in the residential sector (adapted from [99]).

State /reference	Year	Number of participating end-users	Types of DR programs	Percentage of load reduction due to DR programs	
				Peak hours	Off-Peak hours
California/ [100]	2005	~120	CPP	12%	-

California/ [101]	2004	2500	CPP	13%	5%
			CPP	25%	-7%
				41%	13%
California/ [90]	2004	~220	CPP	51%	-
			TOU	-	32%
California/ [102]	2005	~200	CPP	43%	-
			TOU	-	27%
Colorado/ [103]	2006-2007	~3700	CPP	44.8%	0.1%
			TOU	-	10.6%
			TOU+CPP	52.2%	10.6%
Florida/ [104]	2000-2001	~ 2300	CPP	44%	22%
Idaho/ [105]	2005-2006	~ 900	TOU	-	1.84%
			CPP	50%	-
Illinois/ [106]	2003-2006	~1500	RTP	15%	3%
Missouri/ [107]	2004-2005	~500	TOU	12%	-
			TOU + CPP	12%	-
			TOU + CPP	35%	-
New Jersey/ [108]	1997	Not available	TOU + CPP	50%	26%
New Jersey/ [109]	2006-2007	~ 1300	CPP	26%	-
			TOU	21%	-
Ontario, [110]	2006-2007	~500	TOU	5.7%	2.4%
			CPP	25.4%	11.9%
			CPR	17.5%	8.5%
Washington and Oregon, [111]	2005	~110	RTP	17%	-
			TOU+CPP	20%	-

The experiments occurred in the United States (California, Florida, Idaho, Illinois, Missouri, New Jersey) and in Canada (Ontario). In general, two groups were created: a control group maintaining the existing tariff and the trial group subject to a dynamic tariff. The experiments led to the conclusion that end-users indeed responded to the price signals. The consumption pattern changed to achieve bill savings, leading to peak reduction in periods of higher tariff with the application of the CPP scheme. The end-user also consumed more in the off-peak periods since the price was much lower than in the peak. The price signals were found quite relevant in influencing the end-user energy behavior [99].

Since then, DR strategies have received a great interest from utility companies throughout the world, recognizing their role to facilitate the operation of the system, and many governments engaged in policies to promote their application focusing on options that include promoting energy efficiency programs to foster end-user energy behavior changes and the ability to control end-user appliances by rescheduling their operation. In general, these operations do not actually decrease the amount of electricity consumed, but rather shift it to when it is more convenient from the overall system perspective. DR can take place at a fast timescale, contributing to the system stability, the reduction of electricity generation costs and CO_2 emissions [112].

Several studies have been reported in the literature focusing on the management of household energy resources, considering several types of controllable loads, taking into account micro-generation and also starting to include storage systems under a perspective of integrated management of energy resources. However, most of these studies take only into consideration the reality inside the houses. In fact, in face of a low price signal, all local EMS would engage in similar actions (shedding the same type of loads at the same time) to maximize benefits. Since the actual impact of household consumption is noticeable when it is summed up over a large number of consumers, this could lead to instability of the system operation [113,114].

In this context, recent studies attempt combining both perspectives to execute DR activities based on “demand follows supply” strategies, including the provision of AS. In the SG context, the provision of these services by aggregating electricity end-users engaged in DR programs is becoming an attractive alternative.

2.3 Demand Response Aggregators

Several authors have argued that DR is a relevant strategy contributing to the optimal operation of the overall power system, by means of EBAg that are able to interact with in-house EMS controlling flexible loads according to end-user preferences and grid signals, namely via prices and contingency requests. Moreover, EBAg should be able to safeguard the quality of the energy services, provide AS, contribute to cope with the intermittency of RES, and avoid peaks in the load diagram. Some of those relevant studies are presented in [66,115–132].

Most studies consider that certain forms of DR are appropriate to provide AS because of their quick response, decentralized nature and the reliability associated with a large number of small-scale resources [133]. These resources may be able to provide AS cheaper, more proficiently, and with a reduced carbon footprint than conventional generation resources. Moreover, they can hypothetically be brought to market faster than new generation resources, as they do not have to go through lengthy permitting and regulatory agreement procedures as long as they conform to the regulatory dispositions. Those studies have examined the technical capabilities of flexible loads to provide AS including the suitability of specific end-uses [134,135], resource potential [136], control strategies [137,138], measurement and control [139], and strategies for incorporation into competitive markets [140–142]. Additionally, limited field tests of DR resources providing various forms of AS have verified their technical feasibility [34,40,48,143–145].

In [143] the impact of increased penetration of RES generation is analyzed for the balancing authorities to procure more AS. However, while DR resources are technically capable of providing AS, such as frequency control, ongoing experiences across the U.S. have demonstrated that AS provided by DR have relatively negligible players in most regions. The use of DR programs for AS thus requires regulatory policy changes. This section presents EBAg using load flexibility and/or electric energy storage (EES) where the aim is to minimize operation costs contributing to manage electricity costs in the day-ahead and in real-time market, considering load uncertainties, to provide AS to the SO.

2.3.1 Energy Management System Aggregators with Energy Storage Systems

The predicted growth in the use of EV and its capacity to store electricity has been promoting the discussions about the necessity to create intermediate entities that could assist the management of aggregations of EV.

In [146] the concept of a player aggregating EV is introduced assuming that each EV cannot bid in the EM due to its low power capacity. In [147] the concept of a "middleman company" aggregating a significant amount of EV is proposed, in an operation mode in which drivers communicate their driving needs to the aggregator and the aggregator manages this information creating a Virtual Power Plant (VPP), i.e. a system integrating various types of power sources and loads forming an integrated network [148], where the expected number of vehicles to be plugged and the quantity of energy to be available are known.

A similar aggregator agent is mentioned in [146,149–154], where the aggregator is seen as a source of generation or load. In [153] the aggregator is a "command and contracting architecture" providing AS, namely frequency control to fine tune the grid frequency by matching generation and load. The aggregator gets instructions/signals from the SO and sends them to the EVs that are available and willing to sell the service. The EVs can connect/disconnect from the aggregator as they enter/leave the charging station.

In [155] an aggregator of EV is proposed, which is able to use the distributed power of EVs to provide V2G frequency control services. An optimization problem is formulated with control strategies to charge batteries of each EV, involving the charging cost and the reward based on regulation prices, considering constraints regarding to charging requirements, such as energy capacity and desired target state-of-charge (SOC). The decision variables relate to the charging sequence, charging duration and charging rate. To optimal solution is obtained using a dynamic programming algorithm.

Possible architectures are presented in [156] regarding direct communication between the SO and the EV owner as well as intermediate communication via an aggregator. It was concluded that this latter architecture is the best solution since the aggregator is permanently available being possible to contract reserve services continuously, while single EVs present less availability during large periods of the day for V2G. The first architecture option is less reliable than the second one, since it is not possible to control the behavior of EV owners, although it is possible to influence them with reward schemes. The second option is more reliable since the aggregator is able to control the EVs for V2G through the contracted fleet size and available capacity. An aggregator agent for EVs that bids (energy) in the day-ahead and intraday EM is proposed in [153], working as an interface that exchanges information between EVs and an "energy hub agent", that is an agent able to manage a control area. The key purposes of this aggregator are the detection of the EV connection, the estimation of the available energy in the EV fleet and its dispatch.

Considering that load participation in the EM can contribute for the avoidance of network congestion and reduction of line losses, the proposal in [157] focuses on creating an optimal EV charging strategy and developing a decision support tool for demand-side participation in the EM. This scheme should be responsive to the congestion of the local distribution network, while addressing the sequential day-ahead and hour-ahead markets by modeling the interaction of aggregators participating in the transmission level of the wholesale EM with its Smart Microgrid Affiliates (SMAs) linked to the SO.

Facing the energy prices and load uncertainties, [158] develops a Model Predictive Control (MPC) approach based on scheduling and process strategies for the load aggregator that is participating in the wholesale EM to purchase electric energy to serve their customers, with and without EES. Three different MPC scenarios are created: for distribution system without EES where the load is inelastic and determined by the customer, in which the scheduling and operation strategy has very limited flexibility; for distribution system with EES, used according the day-ahead forecasted load and energy price, in which the scheduling and operation strategy is more flexible; and for distribution system with EES that utilizes the real-time update price and load forecast to determine optimal operation. The basic approach of MPC is a finite-horizon optimization determining the series of optimal control operations solved before each control step, and a linear programming model is used to solve the real-time electricity cost minimization problem [158–160].

An algorithm to be used by an aggregator of EV to optimize V2G provision of energy from EVs to the SO and AS scheduling, namely load regulation and spinning reserve, is developed in [144]. The algorithm maximizes the profits to the aggregator while offering more flexibility via peak load reduction to the system and low cost of EV charging to the end-user. The mathematical formulation takes into account the temporal uncertainty of the EV and the algorithm simultaneously schedules charging and AS provision to reward the EV owner for their participation.

The data driven potential of EV loads to harnessing demand flexibility is presented in [161,162], demonstrating that the conventional charging policies have high peak-to-average ratios of the aggregator demand and absence of link with wind generation. The authors show the importance of flexible loads in the exploitation of RES by changing the load patterns and reducing the effects of the intermittency of RES with simple local information focusing on load flexibility as a strategic way to enhance RES penetration and promoting policies complying with the end-user preferences.

Simulation and optimization methods for an aggregator are developed in [163], involving DER, thermal energy storage and DSM to create a VPP. The objective function of the optimization problem is minimizing total costs, which implies maximizing the profits of energy generation of thermal units in the day-ahead market, and consequently offering lower energy costs to the end-user. The optimization takes into account technical constraints and the reduction of load in peak hours.

A hierarchical coordinated charging framework for EVs through four aggregators is proposed in [164]. Each aggregator has several EV contracted and is responsible to optimize their charging needs. In this way, each aggregator should know the charging preferences of the EV owners and the local transformer capacity limits. Based on this information a linear optimization model is developed to determine the charging curve of each aggregator according to DSO requirements as a centralized coordination. Each aggregator takes this curve into account and uses a fast heuristic algorithm to allocate the state of charge of each EV combining it with the power curve suggested by the DSO. The aggregator is compensated by the DSO through a straightforward cooperation scheme based on the amount of shifted power load.

Assuming that the correlation in the day-ahead between EV aggregators and wind generation companies is a challenge for the system, a stochastic optimization model based on mixed-integer linear programming (MILP) is developed in [165] to determine the bidding strategy to minimize the difference between the energy production of wind generation companies and EV consumption, optimizing the scheduling of batteries charging. The objective is to maximize the EV aggregator revenues from selling the wind energy and regulation capacity in the day-ahead market minus the charging cost and the energy imbalance, including constraints as the capacity of batteries and preferences of EV owners for the SOC.

A model that optimizes the performance of an EV aggregator in the EM in the long-term is presented in [166], managing the charging and discharging of the EV batteries to maximize EV owners profits considering TOU tariffs. A formulation is also proposed to evaluate the degree of willingness of the end-user associated with the aggregator to provide AS during a specific period, by optimizing the charge and discharge of EVs submitting the best bidding strategies in the day-ahead and real-time markets. The uncertainty associated with the utilization profile and behavior of EV owners as well as uncertainties in EM prices are taken into account, including the behavior of market players regarding prices and revenue schemes to attract the participation of EV owners. A stochastic programming approach is used to model the ability of competitors to attract EV owners and evaluating customer satisfaction [152].

A self-scheduling model for an EV aggregator is proposed in [167], for which the main aim is deciding the purchase of energy in the day-ahead market and the offers of AS, as balancing services, to a wind power producer. The stochastic model represents the charge and discharge of EV batteries and several scenarios with different AS requests from the wind power producers and driving preferences of the EV owners. A bi-level optimization problem is formulated that is transformed in an equivalent MILP. The upper level consists of minimizing the EV aggregator cost (purchasing electricity, battery degradation) and the lower level consists in maximizing the consumer and producer surplus. The authors conclude that an EV aggregator can provide AS to compensate for forecast uncertainties of wind generation.

An optimal scheduling of load and operation strategy is described in [168], using EV batteries managed by a aggregator. The aggregator bids in the day-ahead market to maximize its profits, taking into account the forecasted demand and price uncertainties in real time. The aggregator uses the EV batteries to help in achieving a balance as a consequence of forecast failure. Two main scenarios are dealt with: one considering a fleet of one thousand EV and another one without EVs.

An optimization model formulated as a deterministic MILP for a load aggregator in the commercial sector is developed in [169], in which the objective is to allocate flexible loads to minimize the total energy costs for the consumer. The optimization uses physical-based models of each end-user, namely loads and a stationary ESS. It concludes that presently stationary ESS are not an effective investment due to the battery inefficiency and high prices.

The dissemination of EBAg has been strongly focused on the contribution of EES, including the participation of EV to help the system achieving a balance between supply and load [167,168,170–173]. The next section presents EBAg approaches in which EES do not play a prominent role.

2.3.2 Energy Management System Aggregator Offering Load Flexibility

In this section demand/load aggregators are presented, which use the load flexibility provided by the end-user through DR strategies with the aim to offer AS to the SO also giving economic benefits to the end-user, which is summarized in Table 2.

A methodology considering both the short and long-term operational and investment costs of providing load flexibility is presented in [174], analyzing how end-users can respond to requests from the SO. An aggregator able to connect with smart appliances is proposed for assisting network management and promoting a cost-effective integration of RES. In [175] the challenges and approaches to using responsive loads to supply AS in SG are discussed, taking into account the required response duration and time of operation. The benefits of providing AS from loads instead from generation are assessed, along with the capability to reduce losses, increase transmission capacity and generation capacity. In this setting, a key challenge that is identified in the development of SG is the need to reduce communication latency when interfacing various communication systems to control a large number of small loads.

In a series of works, the problem of DR is mapped to that of selfish routing over parallel links, with each link corresponding to a timeslot. The proposals in [176,177] consider a set of users that have to schedule their demands within a finite horizon. Users have a utility function depending on the energy consumed and are charged for this consumption by the SO. Thus, for given prices, each user can calculate the consumption pattern that maximizes its net utility. Under the assumption that the SO objective is to maximize social welfare (total utility minus the cost of supply), distributed algorithms are developed based on control mechanisms and dual decomposition methods. In a similar framework, a two-time scale wholesale EM is considered, where power may be purchased either through a day-ahead market or in real-time [176–178], assuming a social-welfare maximizing SO that communicates and negotiates directly with the utility and end-users. In this case, the optimal strategy is to set prices equal to the marginal cost of supply. However, this does not hold for a scenario where a self-interested SO seeks to minimize its operational cost. This has been considered also in [179] that investigates the problem of demand scheduling from the SO's perspective. The DR scenario of a cost-minimizing SO that incentivizes home users to shift demand through dynamic pricing was considered in [180]. In addition, several works cast the problem of DR as a Walrasian auction[4], where prices are set to match supply and demand and use "*tatonnement*" mechanisms for its solution [181]. These models consider price taking residential end-users that schedule their consumption throughout the day and an SO that sets prices to maximize social welfare. A similar "*tatonnement*" process has been proposed in [182] for the stochastic version.

All the works mentioned above require extensive message exchange between the SO and the end-users. Hence, scalability issues may arise in a large-scale deployment. Hierarchical market structures, where EBAg serve as DR intermediates, appear as a promising approach to deal with scalability issues. In [183], it is proposed that the EBAg should coordinate electricity generation and DR.

A simplified hierarchical market mechanism is proposed in [184], where the SO sets a target demand curtailment and the aggregator offers compensation to the end-users to meet this target at minimum cost. Each end-user is a price-taker and bids its supply function in order to minimize its disutility. In this setting, two bidding techniques were designed that converge to the optimal solution. These works do not take into account incentives and consequently do not capture the interaction of competing aggregators. Considering the interaction of several EBAg, for a microgrid scenario, a two-phase market model was proposed [185], where in the first phase a "*tatonnement*" process is used to decide the price paid by the SO and the energy provided by each EBAg. For the second phase, a supply function bidding technique is proposed, where the microgrid bids supply functions and the EBAg sets the price to maximize its profit. While [185] focuses on microgrid generation within a particular time slot, [49] focuses on the time schedule of residential loads. The importance of DR in the residential sector was also quantified in [186], where it is shown that a slight extension of 10% in the total operation time of residential loads may reduce peak consumption by 125 MW. The model consists of a set of competing aggregators, where the aim of the SO is to minimize operational costs giving prizes for the aggregators that contribute to achieve this objective. The aim of the aggregator is to maximize its profits giving compensations to their associated end-users for changing their consumption patterns. The aim of end-users is to maximize the tradeoffs between the income obtained from the aggregator and the discomfort for changing the energy consumption behavior. Game theory and benchmark scenarios are used for this purpose. The access to end-user energy

[4] A Walrasian auction is a type of simultaneous auction where each agent calculates its demand for the good at every possible price and submits it to an auctioneer. The price is then set so that the total demand across all agents equals the total amount of the good. Thus, a Walrasian auction perfectly matches supply and demand. Walras suggested that equilibrium is achieved through a process of *tâtonnement* (French for "trial and error").

consumption behavior information is essential to better exploit the DR benefits in the SG context and the DR strategies, and therefore mechanisms for this purpose need to be investigated [49].

Considering that load flexibility is the best resource to provide fast AS, namely primary and secondary FC, [187] proposed an aggregator that provides AS based on scheduling flexible load taking into account restrictions for the utilization of appliances. In [188], a hierarchical framework for a load aggregator was presented, which is an intermediate between TSO and electric storage space heating systems in the residential sector.

In [189], it is considered that DER and (flexible) thermostatic loads should participate in the real-time operation of transmission and distribution grids, using the VPP concept. The authors developed an optimization model based on DLC to manage a VPP and compute optimal control strategies to be applied to controllable devices to obtain the maximum load reduction over a specified control period. An aggregator determines the load reduction capability over a specified control period to define the corresponding load reduction bid to be presented in the EM to reduce congestion and differences between load and supply.

Considering the adaptation of load to the EM changing condition, a multi-layered and multi-directional information exchange framework is developed in [190], creating an adaptive load management system able to implement DR. The system is decomposed in three layers: the primary layer (bottom level) is composed by end-users; the secondary layer (middle level) is composed by load aggregators as load serving entities; the tertiary layer (top level) is composed by the SO. The optimization of the system as a whole is made in this layer. For this purpose, techniques based on Lagrange decomposition are used to formulate the optimization problem with demand functions for each end-user, with a given uncertainty degree, to better inform the other layers about the end-user's preferences on electricity consumption [190–193].

The role of an EBAg is presented in [194], which is a mediator between the end-user (local energy box - LEB) and the SO allowing the coordination of a large-scale dissemination of in-house DR devices. The EBAg is aimed at using the demand-side flexibility provided by clusters of end-users to provide system service requirements, involving lowering or increasing the power requested in each time slot within a planning horizon. This contributes to balancing load and supply, avoiding peaks in the load diagram, and coping with the intermittency of RES, thus increasing the overall system efficiency by offering an attractive alternative to supply side investments on peak and reserve generation. For this purpose, an MOO model was developed to maximize the EBAg profits, taking into account revenues from the SO and payments to end-user clusters, and minimize the inequity between the amounts of load flexibility provided by the clusters to satisfy system requests. An approach based on a genetic algorithm coupled with a differential evolution algorithm is proposed to deal with this model.

Taking into account the problem of optimally scheduling appliances in households considering time differentiated electricity tariffs and rewards to the end-user from an energy aggregator, [19] developed a MILP model and an algorithm, which is based on a heuristic scheme that combines local search and exhaustive enumeration stages, where the aim is to minimize the overall cost in the load rescheduling, taking into account end-user's comfort preference. This approach allows to explore a significant subset of the solution space, with limited computational burden, although it does not consider the schedule of appliances in a limited time horizon [195].

A trading framework permitting the DR aggregator to get load flexibility from end-users and sell it to "purchasers", i.e. buyer in EM, is proposed in [196], via a power purchase agreement, i.e., a contract between the seller and the buyer of electricity [197]. The DR aggregator presents TOU tariffs to the end-user and gives rewards based on the load flexibility provided. The reward scheme consists of a stepwise function, the higher the amount of load reduction the higher is the reward. The aim of the DR aggregator is to maximize its profits (revenues for selling load flexibility to the purchaser and costs to reward end-users). The model includes a mixed integer profit function, and the case study was based on the Australian National Electricity Market. The authors conclude that bidirectional exchanges of energy between end-users and the purchaser is a major future challenge that should take into consideration the uncertainties of the energy consumption behavior [196]. Afterwards, in [198] the authors modeled the behavior of a DR aggregator taking into account wind power uncertainty. The aim of the DR aggregator is to maximize its revenues and the problem was formulated as a bi-level programming model, in which the upper layer deals with the wind power producer and the lower layer deals with the DR aggregator, which is modeled through a revenue function. The bi-level problem was then configured into a single layered mathematical problem with equilibrium constraints using a mixed integer programming approach and solved using CPLEX [199] and GAMS [200] for a scenario based on the Nordic Electricity Market [201].

The German EM based on the balancing mechanisms demonstrated that DR is impacted by: minimum bidding volume, minimum bidding duration and bidding up and down offers. New DR services will open the door for end-users to manage and adjust their consumption as well as to reduce their energy bills. Although it is difficult to forecast at this stage how significant is the role that demand side flexibility will play, in order to guarantee a level playing field for all market participants and unlock market access for end-users and aggregation agents, market rules will need to be adapted to enable them to participate in the EM [202].

The implementation of SG offers a business prospect for SO and energy traders to implement DR programs [203], since those entities can maximize their profits trading flexibility provided by end-users on the EM using an aggregator service platform. These authors designed an architecture based on an ICT platform providing management, forecasting, aggregation and load scheduling of a large number of end-users, being a scalable infrastructure that allows the implementation of residential DR programs, with a VPP at the core of the system named SEMIAH – Scalable Energy Management Infrastructure for Aggregation of Households. To validate this new infrastructure and assessing its potential impacts, a large-scale simulation of 200,000 households was performed. They concluded that the remuneration schemes given by the aggregator to the end-users for their load flexibility would lead to a more secure and sustainable energy supply.

Table 2 – Energy Management System Aggregators Models

Refer.	Manage	Requests/Constraints	Reward Scheme	Objective Function	Algorithmic Approach
[88]	Storage	PS/EM	According to EV available power capacity	Maximize the aggregator revenue	Dynamic programming
[121]	Load (Thermostatic appliances); Micro-generation	PS/EM		Maximize load reduction over a control period;	Integer Linear Programming
[136]	Storage (V2G)	PS/EM		Maximize revenue	Dynamic programming to compute the optimal charging control for each vehicle
[86] [137]	Storage (EV)	PS/EM; End-user/ EV owner		Day-ahead and intraday with supply and demand energy bids	
[90]	Load (Thermostatic appliances); Storage (EV)	PS/EM		Minimize EM costs	Stochastic dynamic programming, for the real-time and day-ahead markets.
[91]	Storage (EES)	PS/EM		MPC: Scheduling and operation strategies in day-ahead and real-time power markets with different levels of price and load uncertainties	Linear programming and stochastic optimization
[28]	Load	PS/EM		(1) Regulate frequency; (2) Minimize the amount of responsive loads manipulated	Dynamic model in MATLAB/Simulink®
[127]	Load	End-user/ EV owner		Minimize a convex combination (overall electricity costs, scheduling preferences and indoor comfort)	MILP and heuristic algorithm
[27]	Load	PS/EM		TIMES – The integrated Markal Efom System	Energy Technology System Analysis Programme (ETSAP)
[123]	Load			Multi-layered adaptive load management (ALM)	Lagrange decomposition technique
[113] [30]	Load	PS/EM	For aggregator to end-user; For aggregator to end-user	SO: Minimize operational costs; Aggregator: Maximize profits; End-user: Optimize tradeoffs between income and discomfort;	Optimization model
[120]	Load; Storage			Minimize energy payments	CPEX solver in GAMS
[4]	Load	PS/EM; End-user/ EV owner	Reward and penalties from the SO and end-user	Maximize EBAg profit, minimize the inequity of load flexibility by end-users	Genetic Algorithm and Differential Evolution

[102]	Load (commercial sector); Storage			Minimize end-user costs	Deterministic mixed integer linear programming
[96]	Load; Storage; Micro-generation	PS/EM		Minimize total costs	Mixed-integer quadratic programming; Lagrange relaxation
[99]	Storage	PS/EM; End-user/ EV owner	Reducing the electricity price	Maximize aggregator profit	Stochastic programming: Multi-agent systems and dynamic game theory
[98]	Storage	PS/EM (local farm of wind generation)		Minimize the difference between wind generation and EV consumption	Stochastic programming, MILP
[97]	Storage		Cooperation compensation mechanisms from DSO to aggregator	Minimize electricity purchasing costs; Minimizef peak loads	Linear programming combined with heuristic algorithm
[100, 138]	Storage	PS/EM; End-user/ EV owner		Minimize aggregator costs; Maximize consumer and producer surplus	Mixed-integer linear programming
[128]	Load	PS/EM; End-user/ EV owner	Based on the load provided by the end-user	Maximize aggregator profits	Mixed-integer profit function
[130]	Load	PS/EM; End-user/ EV owner		Maximize aggregator profits	Bi-level programming, Mixed-integer linear programming

2.3.3 Energy Management System Aggregators Companies

Some demand aggregator companies offer electricity end-users the possibility to take part in DR activities using their load flexibility. Examples in the USA are: EnerNOC, Comverge, Inc, CPower, EnergyConnect, Energy Curtailment Specialist (ECS), and North America Power Partners (NAPP). These companies establish individual contracts with their customers, the end-users of electricity. In Europe there are energy service companies leading aggregator field tests in Austria, Finland and Sweden. Table 3 displays some features of these projects, namely the main objective of the aggregator, the customer portfolio, and an overview of technologies used to implement the DR programs.

Table 3 – Companies in USA and Europe with EBAg of load flexibility [98]

State or Country/ Company /Reference	Aim	Customer portfolio	Strategy/Technologies
Massachusetts/ EnerNOC / [204]	Energy management services, namely DR program design and implementation	Large customer (<1GW): Industry, commercial, services. Aggregated power: ~1,000MW.	Direct control by EnerNOC from operation center through customer EMS
Georgia/ Comverge/ [205]	Install and control smart thermostat at the customer premises; sell DR to utilities and SO	Residential and small customer Aggregated power: ~500MW.	Smart thermostat and web-portal. In 2010: 2.5 M load control devices installed
Manyland /CPower/ [206]	Strategic energy asset management to increase customer revenues	Large customer. A total of ~2,000MW of aggregated power.	Remote operation web-based energy management metering.
California/ Energy Connect/ [207]	Energy Automation Service provider	Large customer (<1GW): Industry, commercial, government	Energy automation, metering and communication
New York/Energy Curtailment Specialist (ECS)/ [208]	Sell DR to utilities and SO	Large customer: Industry, commercial, services. Aggregated power: ~1,000MW.	Metering and metering software, control center
New Jersey/ North America Power Partners (NAPP) /[209]	Sell DR to utilities and SO	Industrial and commercial Aggregated power:~500MW.	Web-based platform for monitoring and self-scheduling
Austria/ [32]	FC from electrical water heaters . Sell DR to TSO (Austrian Power Grid AG)	Residential end-user provide load flexibility from electrical heaters	Remote control. Independent metering and communication (via SMS). Profit sharing between aggregator and end-user.
Finland/SEAM/[210]	FC from demand response. Aggregates and assists end-customers providing capacity to the reserve. Sell DR to TSO (Fingrid)	End-customers (commercial): Provide capacity to FCR mainly from ventilation equipment.	Profit sharing between aggregator and end-user. Load control of HVAC systems
Sweden/ Ngenic/ [211]	Control of heat pump. Sell flexibility to DSO, TSO, suppliers/BRPs	Residential sector	Temperature sensor, communication to the control and temperature forecast. Machine learning algorithm which “learns” the thermal inertia.

Most implementations of DR programs are for large customers; only Comverge, Inc. and Ngenic address the residential sector using smart thermostats and controlling the temperature in house to satisfy utilities and SO requests.

EnerNOC and EnergyConnect, Inc. follow a specific procedure to design and implement DR programs: first an energy audit is made in the customer installation to evaluate the capability to participate in DR programs, then the loads that are flexible and can be controlled are identified, the amount of power that is available to be managed and in which periods it is defined, and then an estimate is made of the economic benefits for the customer to participate in the DR program as well as the investment needed to implement the DR strategies. While the project is under execution, an energy manager focuses on monitoring and control actions to reduce energy consumption, creating energy efficiency recommendations to improve the economic benefits.

Cpower is an energy service company (ESCO) aiming to reduce loads in peak periods by controlling the load in real time. ECS installs a meter for free at customer's facility to help managing the energy usage more efficiently by displaying the consumption and associated cost in real time. NAPP offers a DR service provider from customers, giving financial incentives based on the kW of load reduced to decrease load once a month for 15 minutes. It follows the same process as EnerNOC and EnergyConnect, Inc.

In Austria, electrical water heaters (2 kW) are the target loads in the residential sector, the communications being established between the aggregator and the end-user via SMS. The water temperature is monitored with a frequency of minutes, and the aggregator remotely controls the heater through a control relay, with a temperature sensor and a cellular device. In this way, the load operation is shifted in time without causing discomfort to the end-user, and the aggregator can turn on all water heaters in sequence to provide a service during a certain period of time. A partnership with a telecom utility in Austria was established to provide the communications infrastructure between end-user and the aggregator [32].

SEAM is an aggregator company from Finland [210] working in the day-ahead, the intraday and the balancing markets, including frequency control reserve. The procurement procedure for load control is divided into two auctions: yearly, remunerated based on a fee, and hourly, approximately 400€/MW demand cut. The profits obtained are shared between the aggregator and the end-user. The participant customers are large consumers, namely commercial buildings to control the ventilation in cycles of around 3 minutes, which can be rescheduled without discomfort being noticed by the users (due to the inertia in air quality).

Ngenic is an ESCO from Sweden, which develops technologies enabling to control heat pumps remotely, to minimize the consumption by scheduling the load according to temperature forecasts and using thermal inertia to store heat. An algorithm minimizes the electricity consumption according to price signals (€/kWh), thus minimizing the cost for heating [211].

2.4 Concluding Remarks

In this chapter the key characteristics of DR programs and models for the development of EBAg were presented. This survey focused on the challenges, potential advantages and (technical and policy) barriers that are at stake regarding the implementation of DR programs using EBAg to provide AS requested by the SO. These barriers should be addressed to make the most of SG features to enable more cost-effective decisions for the efficient operation of the grid with high shares of RES.

The ongoing transformations of power systems, concerning the dissemination of distributed generation and the evolution towards SG, pave the way for the implementation of load follows supply strategies to cope with the penetration of RES and ensure an adequate level of power reserve. Load management has received special attention from researchers and policy makers as an effective tool to reduce the need for additional generation capacity as a backup for volatile RES supply and face disturbances and congestions occurring in the grid. Therefore, DR is increasingly important as an enabling strategy for the successful integration of RES, in a perspective of integrated energy resource management, involving controlling flexible loads according to (price and/or emergency) signals from the SO and end-users' preferences.

In this context, EBAg recently emerged as new entities acting as mediators between end-users and the SO in the EM. In a first stage EBAg, as VPP, were devoted to managing EES resources to store the electricity not dispatched, avoiding instabilities in the system. Due to the proliferation of smart appliances, EBAg were extended to other types of loads using DR to exploit the flexibility potential of end-users regarding the usage of some loads and promoting their access to the EM by selling load flexibility and benefiting from rewards or lower energy bills.

Attention should be paid to the contracts underlying the relationships between end-users, the EBAg and the SO. In principle, the EBAg should establish bilateral contracts with end-users and the SO, with the obligation to deliver to the SO the requested load flexibility according to the availability expressed by the end-users involving a certain amount of power in specific timeslots. A thorough definition of the remuneration scheme is necessary as a way to engage and achieve the loyalty of end-users to the EBAg, guaranteeing the implementation of the required changes in the load diagram through specific devices or the change of energy consumption behaviors. Therefore, end-users should receive rewards for load availability, the load changes effectively provided, and also penalties for not complying with load change commitments. Although some studies take the reward schemes into account [155,164,166,175,194,196], most studies just address the advantages associated with the electricity tariffs applied.

The load flexibility offered by an EBAg allows a better management of the power system according to the SO requests to match the supply availability in specific areas and periods, taking into account local RES.

The EBAg requires efficient ICT infrastructures, incorporating features associated with the IoT, to interact with end-users endowed with home EMS to exchange data and send control signals to manage loads. These EMS should be able to monitor and control appliances in the house through robust and low-cost communication infrastructures and protocols. The communication of the EBAg with local EMS and the SO requires secure and reliable communication infrastructures, offering quality of service support, secure routing, interoperability, and scalability to enable the integration of EBAg in a SG context. Special attention should also be paid to privacy issues arising from the management of metering data, which contains private information and activities or choices of end-users, regarding security vulnerabilities and unauthorized access to data.

Adaptive optimization algorithms should be embedded in the EBAg to compute optimal solutions satisfying the constraints derived from the interests and preferences of all stakeholders – the SO, the EBAg and end-users.

The practical implementation of EBAg still faces challenges and barriers that need to be addressed, namely regarding adequate regulatory frameworks. For this purpose, a strategic cooperation between academia, industry and policy makers is necessary to develop algorithms, technical standards, low cost systems, and schemes of seamless integration with the whole power system.

Part II

Energy Box Aggregator Model and Algorithms

3. Chapter 3 – Multi-objective Optimization Problems

3.1 Introduction

Many real-world problems comprise the need to optimize simultaneously conflicting objective functions addressing multiple evaluation aspects that need to be considered simultaneously to appraise the merit of potential solutions. Those aspects of different nature are often combined into a single objective function expressed in a common measurement unit, generally an economic indicator; however, this combination requires a difficult and arbitrary task: to express an objective function in monetary units when it has a quite distinct nature. Moreover, this impairs the analysis of the trade-offs at stake between the conflicting objectives. In face of the existence of conflicting objective functions, in general, there is no optimal solution to all objective functions simultaneously. In this context, the concept of optimal solution, in single objective models, gives place to the concept of non-dominated solutions, that is, a feasible solution for which no improvement in all objective functions is simultaneously possible; that is, in order to improve an objective function, it is necessary to accept worsening, at least, another objective function value.

The multi-objective optimization algorithms should be able to compute and exploit non-dominated solutions enabling to shed light on the tradeoffs at stake to offer decision support information. In addition to contributing to turn the model more realistic vis-à-vis actual problems, a multi-objective approach intrinsically possesses a value-added role in the modeling process and in model analysis, supporting reflection and creativity of DM in face of a larger universe of potential solutions [212]. Thus, compromise solutions should be discovered in this set by exploring the trade-offs between the competing objectives in order to reach a final recommendation.

This chapter introduces the basic concepts of MOO problems.

3.2 Modelling MOO Problem

The development of a MOO study generally comprises the phases of problem formulation, model building, model optimization, and decision support involving the articulation of the decision maker's preferences.

The existence of multiple, conflicting objective functions generates a set of non-dominated solutions, which represents different trade-offs between those objectives. In the absence of further information, namely regarding the decision maker's preferences, none of these solutions can be said to be better than other belonging to this set.

The MOO problem can be formulated mathematically as the following:

Minimize/Maximize $$\boldsymbol{f_s(x), s = 1, 2, \dots S} \tag{3.1}$$

Subject to $$\boldsymbol{g_m(x) \geq 0, m = 1, 2, \dots, M} \tag{3.2}$$

$$\boldsymbol{h_q(x) = 0, q = 1, 2, \dots, Q} \tag{3.3}$$

$$\boldsymbol{l_p \leq x_p \leq u_p, p = 1, 2, \dots, n} \tag{3.4}$$

$\boldsymbol{x}$ is the decision (variable) vector $\boldsymbol{x = (x_1, x_2, \dots, x_n)}$, $\boldsymbol{g_m(x)}$ is the vector of inequality constraints, $\boldsymbol{h_q(x)}$ is the vector of equality constraints, $\boldsymbol{l_p}$and $\boldsymbol{u_p}$ are the lower and upper bounds of the decision variables, respectively, and $\boldsymbol{f_s(x)}$ is the objective function vector. Images of the decision vectors consist of objective function values defined in the objective space $\mathrm{in}\ \mathbb{R}^{\boldsymbol{s}}$. The image of the feasible region in the objective space is called feasible objective region. Figure 7 illustrates the representation of these two spaces and the mapping between them.

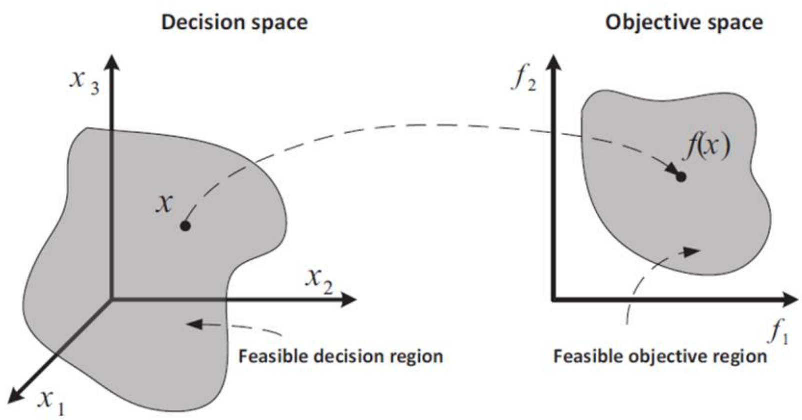

Figure 7 - Representation of the decision space and the corresponding objective space.

The problem has ***M + Q*** functional constraints, ***M*** inequality constraints (3.2) and ***Q*** equality constraints (3.3), and ***n*** decision variables, $\boldsymbol{x = (x_1, x_2, \ldots, x_n)}$ with lower and upper bounds. The solution $\boldsymbol{x}$ is feasible to the problem if and only if it satisfies the ***M + Q*** functional constraints and the decision variable bounds. The set of all feasible solutions to the problem is called feasible region $\boldsymbol{X}$.

When solving a single-objective optimization (SOP) problem (*S*=1), the aim is to determine the feasible solution that gives the best value for the objective function; this value is unique, even when alternative optimal solutions exist. According to the characteristics of the objective function, constraints and decision variables, various types of problems exist, which can affect the choice of the methodologies to solve the problem. The problem may become harder, or even impossible, to solve to optimality in case (some or all) variables can assume only discrete values, objective functions and/or constraints are strongly nonlinear, etc.

3.2.1 Pareto Optimal Front

The Pareto optimal front concept is fundamental in MOO. The Pareto optimal front, also called non-dominated front, consists of solutions for which none of the objective functions can be improved without degrading, at least, one of the other objective function values.

MOO methods should be able to guide the search for the Pareto optimal front and to ensure its characterization in the most complete way possible to have representative solutions of different trade-offs to be made between the objectives. Although the primary purpose is common to any optimization algorithm, the second is an MOO specific issue; since no solution of the Pareto optimal front can be considered better than another, it is important that the algorithm finds representative ranges of distinct solutions, which can allow a good characterization of the trade-offs at stake.

In complex models, e.g. of combinatorial or/and nonlinear nature, the Pareto optimal front can be determined by making a population of solutions evolve using different techniques. There are methods that order the population of solutions by non-dominated fronts. The non-dominated solutions are placed in the first front, and then the non-dominated solutions of the remaining solutions are placed in the second front, and so on. In each front all solutions are dominated by at least one element of the previous front.

An illustrative example of a problem with two functions (e.g., cost and losses) to minimize and a set of Pareto front solutions is presented in Figure 8.

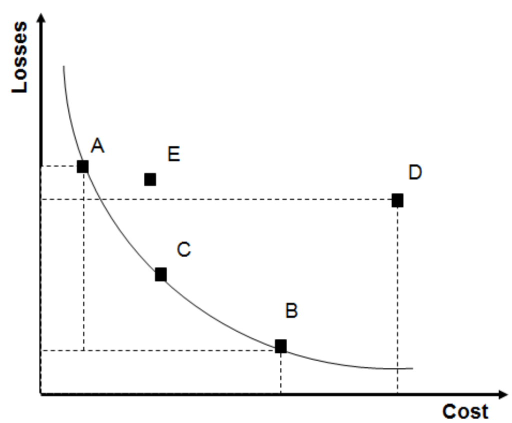

Figure 8 - Pareto Optimal Front - MOO

For instance, the point ***A*** on the Pareto front represents a non-dominated solution of lower cost, but with significant losses; the point ***B*** represents a non-dominated solution of higher cost with a lower value of losses. It is impossible to say that solution ***A*** is better than ***B*** or the opposite without using preference information elicited from the decision maker. There are many other non-dominated solutions in the front, for example solution ***C***, whose values of cost and losses establish another compromise between the objectives. Points ***D*** and ***E*** represent dominated solutions of the problem; that is, there are solutions on the Pareto optimal front that are better than ***D*** and ***E*** for both objective functions.

Searching for non-dominated solutions to the MOO model may require a careful analysis of both the decision variable and the objective function spaces. For instance, a certain displacement in the decision variable space may not correspond to a similar movement in the objective function space. Then, it is necessary to map the behavior that the algorithm presents in the decision space into the objective function space. In some algorithms, the behavior exhibited in the objective space is used to guide the search in the decision space. Algorithms should in some way coordinate the search in both spaces, so that the generation of new solutions in the decision space is translated into the expected characteristics for the solutions in the objective space.

The choice of a final solution to the MOO problem is generally understood as the identification of a compromise solution in the set of non-dominated solutions that best corresponds to the preferences expressed by the DM. In some cases, the main purpose is the characterization of the non-dominated solutions in the most comprehensive manner possible.

3.3 Evolutionary MOO Algorithms

This section will discuss some of the most prominent approaches developed for solving MOO problems, with special focus on EA and Differential Evolutionary (DE), both used to solve the EBAg MOO model presented in Chapter 4.

The adoption of principles based on the natural evolution has gained importance since the 1960s, specifically using Darwin's theory as an analogy in the realm of optimization, consisting in the preservation of the characteristics of the best solutions in the population to give rise to solutions for the next generation [213]. EA are search and optimization techniques inspired on genetic evolution mechanisms of adaptation and survival of the fittest. In general, EA do not make requirements in terms of continuity, convexity or differentiability of the functions or search spaces. EA stands for a class of stochastic optimization methods that simulate the process of natural evolution that have been proving both efficiency, regarding the computational effort involved, and effectiveness, concerning the quality of results, in solving difficult optimization problems, namely with combinatorial or/and nonlinear features. Since EA work with a population of solutions, they have gained special relevance to solve MOO, in which the aim is to converge to the Pareto optimal front [214], instead of having to perform multiple optimization runs with different parameter setting as it happens in the majority of mathematical programming methods for MOO [215]. We use the designation EA to encompass broadly also genetic algorithms, evolutionary programming and evolution strategies, which have particular characteristics.

In general terms, the structure of an EA follows the steps:

- The evolutionary process starts with the generation of an initial population of solutions, which can be done in a random manner or using some problem context knowledge.
- The solutions are evaluated according to a fitness function, that is, the merit of a solution in relation to the objective functions or the position of the solution to achieve certain aims, which measures their quality and thus is used to guide the search for new solutions [216]. The fitness assignment mechanisms are: dominance-based (determine the fitness of an individual/solution based on the Pareto dominance concept); scalarizing-based (consists of the aggregation of the multiple objectives into a single objective function in order to assign a fitness value to each individual of the population); and indicator-based (performance indicators to give a fitness value to solutions in the current population).
- A set of operators is applied to all or part of the population to create a new population for the next generation (iteration):
    - Selection - to select solutions from the current population to be subject to the genetic operators crossover and/or mutation or to select the solutions that will integrate the next generation population. As in natural selection, more apt solution (with better fitness) have a higher chance of survival and pass their characteristics to their offspring;
    - Crossover or recombination - to combine characteristics of two or more (parent) solutions to create one or more (descendant) solutions, hopefully fitter than their predecessors;
    - Mutation - to introduce changes at specific points (possibly randomly determined) in the structure of some solutions;
    - Replacement - to replace some solutions for the solutions modified with the crossover and mutation operators. Solutions with higher fitness are more likely to

stay in the population and those having a worse fitness have greater probability to be removed.

This process ends when a stop condition is reached, usually the maximum number of generations or the absence of improvement of the population (e.g. the best individual or the average) between consecutive generations.

Since they deal with a population of solutions and the aim is normally identifying the Pareto optimal front, EAs endowed with mechanisms to maintain the diversity of solutions present a major advantage in comparison to the use of scalarizing techniques commonly used in mathematical programming methods [217]. A Pareto front is found throughout the evolutionary process, which hopefully converges to the true non-dominated front for the problem under study. In real-world problems, typically a potential Pareto front can be found; however, no theoretical tools exist guaranteeing its true Pareto optimality. Guaranteeing the diversity of solutions in the Pareto front in order to display the range of trade-offs between the conflicting objective functions in different regions of the search space is an essential aspect of Multi-objective Evolutionary Algorithm (MOEAs) [218]. This feature is usually important to offer to the DM a broader view of the compromises that can be established in diverse regions of solutions with different features.

3.3.1 Genetic Algorithm - Based Approach

The concept of GA was first introduced by Holland in the early 1970s. As the name suggests, GA is inspired on the process of natural selection and genetics, using probabilistic computational models. A comprehensive description of GAs can be found in [213,219,220].

According to the findings presented by Darwin [221], the natural evolution process occurs based on two mechanisms: selection and reproduction (genetic variation). Selection ensures that the fittest solutions, the ones that have higher capability of adapting to the environment, have major probabilities of survival, being able to reproduce more often and giving origin to offspring with fittest characteristics along the successive generations.

In GA, each individual represents a potential solution to the problem and is evaluated according to its performance in relation to the problem evaluation function (which can be just the objective function or integrate further elements of analysis such as a penalty term to penalize infeasibilities). Based on the result of this evaluation, the genetic operators generate new solutions leading to the next generation. A GA works with a set of potential solutions that compete to be selected to generate the parents of the next generation. A new generation is created through operators that aim to replicate the genetic mechanisms. By recombining parents, new solutions are obtained maintaining some features of their predecessors, being the descendants a combination of the parents. Through mutation, new genetic material is introduced into the descendants, which allows the emergence of new features in the new generations.

As it can be seen in nature, it is aimed that the evolutionary process generates populations presenting increasingly better solutions according to the aim of the optimization problem. Expectedly, the average quality of the population increases over generations.

Considering some population P with NP solutions, a simple GA can be described as:

Algorithm 1

```
START
t=0;
Generate an initial population P(t)
Evaluate the solution that compose the initial population P(t)
Repeat:
        Select parents P'(t) based on P (t)
        Apply the genetic operators to P'(t) in order to obtain a new population P(t+1)
            Crossover P'(t)
            Mutation P'(t)
            Select individual to be inserted in the new population P(t+1)
        t=t+1
Until stop condition is verified
END – Final population
```

The evolutionary process is repeated until a certain stop condition is reached, for instance a maximum number of generations is achieved or the population quality stagnates.

In each generation the population is evaluated and the solutions of the population are selected according to their performance. In a MOO setting, the evaluation procedure of each individual in the population requires assessing its merit in the various aspects of the evaluation that are made operational by the objective functions. The selected solutions are recombined through the crossover operator and altered by the mutation operator to produce the offspring.

The main concepts underlying some of these steps will be discussed below, such as encoding (representation) of solutions, fitness, selection mechanisms, crossover and mutation genetic operators, replacement mechanisms, stopping criteria, diversity preservation and elitism.

3.3.1.1 Solution representation

In general, the first step to apply a GA is to create a link between the original problem and the space where the evolutionary process happens [222] through the representation, or encoding, of solutions.

The representation most frequently used, which corresponds to the original idea of Holland [219], is the binary alphabet to encode the values of each variable, both in its traditional version or in a version called the *Gray* code. This code allows adjacent values of the decision variables to differ by only one binary digit. The studies of Bäck [223] demonstrate the superiority of the *Gray* code in comparison with the binary code pattern. However, nothing prevents using representations consisting of real numbers, integers and even characters, since in some circumstances these types of representation bring advantages in terms of appropriateness to the problem, accuracy or decrease the computational effort.

3.3.1.2 Evaluation of solutions

The evaluation of solutions consists in the combination of values of individuals of a population corresponding to its usefulness in solving a problem. This association happens using an evaluation function.

The evaluation function associates a fitness value to each individual (genotype), that is, this function returns, for each individual, a numerical value that reflects its merit, which can be used to obtain the individuals rank. While the evaluation function provides a measure of performance for a specific set of parameters, being the assessment of an individual independent from the evaluations of others, the fitness function makes the match between the performance measure and the allocation of reproductive opportunities, being dependent of other individuals.

3.3.1.3 Population

One of the most important aspects is the population size, since this affects both the quality of the solutions obtained as well as the processing time of the algorithm. Populations may be of any size, which normally remains constant throughout the evolutionary process.

Small populations have the advantage of imposing lower computational requirements, but generally present small genetic diversity of their elements, which can lead to premature convergence and poor quality of the solutions obtained. Large populations, in general, allow coping with the lack of diversity and prevent premature convergence, but increase the computational effort of the algorithm.

3.3.1.4 Selection

The selection is carried out to determine the individuals who will be the parents of the next generation through the mechanisms of crossover, and also for the purpose of choosing individuals (descendants) that must survive for the next generation. Probabilistic selection can be made in accordance with the ability of individuals, such that the ones with higher fitness value are more likely to be selected (thus mimicking the selection mechanisms based on the Darwin survival of the fittest principle).

The mechanisms of selection can be based on the proportion of fitness values and the ordering of the fitness values (ranking). The selection ratio mechanism can be based on the individual's own fitness value and the relationship with the fitness values of other individuals in the population. In the case of selection based on ordering, the selection is made considering only the position of individual in the sorted population, without regarding to its own fitness value.

The most common selection mechanisms include the roulette wheel and the universal stochastic sampling methods. The roulette wheel method [213], Figure 9, is a stochastic selection mechanism in which a slice of the roulette wheel proportional to the individual performance is assigned to each individual. Thus, individuals with higher fitness have higher odds of being selected. This method has some drawbacks, namely it may promote reduced diversity and premature convergence, since the fittest individual can be selected many times.

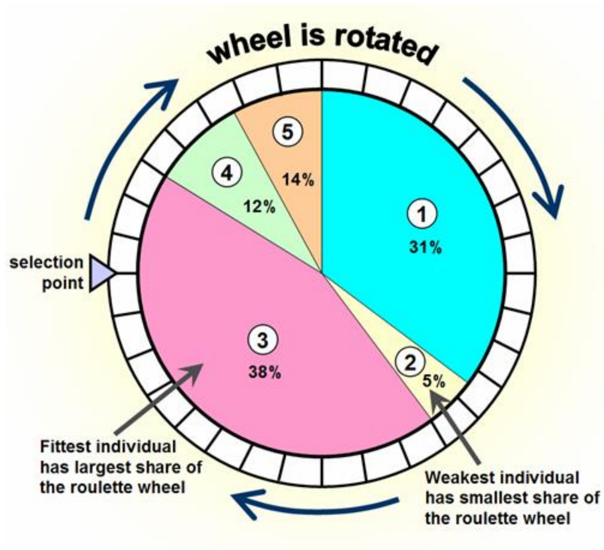

Figure 9 - Roulette wheel selection [224]

In the selection by stochastic universal sampling, individuals are associated with equal and contiguous portions of a wheel. The method is similar to the roulette wheel, the difference being that all the portions are equal, that is, in this case all individuals have the same probability of being selected.

The selection techniques based on ordering include the tournament and the selection by truncation methods. In a tournament selection [213], a number of individuals is randomly chosen in the population and the individual with better fitness value is the winner. The tournament is repeated as many times as the number of individuals to choose. This method avoids premature convergence if the size of the tournament is small, thus preventing the stagnation of the population. In the truncation method, the individuals are ordered according to their fitness values and those whose fitness values are larger than a predefined threshold are selected. In general, the systematic selection of the best individuals degrades diversity.

The balance between convergence and the exploration of the search space is a crucial issue in the design and implementation of evolutionary approaches. Diversity should be maintained to foster exploration but the best individuals across generations should not be lost.

3.3.1.5 Crossover

The crossover mechanism is based on the natural biological process that occurs in sexual reproduction. The crossover operator allows producing new individuals (descendants) from the information of the parents. The underlying idea is to use genetic material (solution components) of individuals (parents) with good fitness values to generate new individuals with superior quality in the successive generations [225,226].

There are several methods of crossover; the most frequently used, according to Baker [227], are mentioned below.

The crossover with a single cut-off point, also called simple crossover, randomly determines a point in the individual representation and exchanges the information at the left/right of that point between the two parent individuals to produce the descendants. In Figure 10, the application of this type of crossover is exemplified considering the cut-off point at position 4.

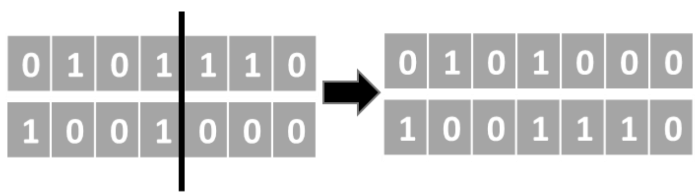

Figure 10 - Crossover with a cut-off point

This operator can be used with multiple cut-off points randomly determined. One of the descendants receives information sequences of odd indexes of one parent and even indexes of the other parent. In Figure 11 the application of this operator with 2 cut-off points at positions 1 and 4 is illustrated.

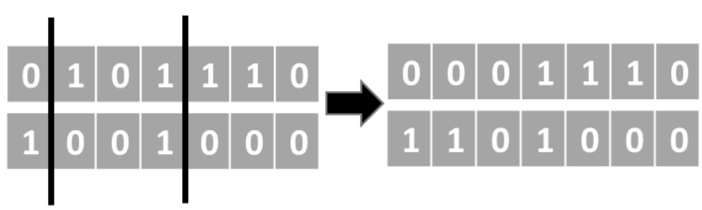

Figure 11- Crossover with multiple cut-off points

The uniform crossover method consists in the use of a randomly generated binary mask onto the parent individuals. One of the descendants inherits the information from one parent in the positions of the mask with a value 1 and from the other parent in positions of the mask equal to 0. The same happens with the other descendant, but with exchanged mask values.

The performance associated with the application of each of these types of crossover operator depends on the type of problem to solve. One aspect that should also be considered when using this genetic operator is the crossover probability assignment. The higher the probability, the greater is the possibility of new individuals entering into the population. The most common values for the probability of crossover lie between 0.6 and 1.0.

3.3.1.6 Mutation

Mutation is a genetic operator that consists of slightly disturbing, typically with low probability, the descendant individuals, in general after crossover. Mutation serves to introduce new information in the population and return lost information to the population. Mutation can consist in randomly determining a position in an individual representation and then replacing the value in that position by other value associated with the representation used. If there is more than one possible value, it should also be randomly chosen. The Figure 12 illustrates the application of uniform mutation to an individual in which the binary digit position 3 has been mutated.

Figure 12 – Uniform Mutation

3.3.1.7 Re-Insertion

After generating and evaluating new solutions, they must be inserted into the population. It is then necessary to decide the number of descendants to be selected and the choice mechanisms of individuals of the current population that will be replaced.

For the first decision, a replacement rate is generally defined, which indicates the proportion of individuals of the current population that can be replaced in each generation. A low replacement rate translates into lower differentiation between generations and implies a slower convergence.

There are several mechanisms of substitution, the simplest one generating the number of descendants equal to the size of the population and replacing the entire population by the new individuals. The new population will then consist of descendants only. This scheme is called pure replacement or re-insertion.

In uniform replacement, descendants are generated in a smaller number than the size of population, replacing randomly chosen individuals of the current population.

The replacement can also ensure that the best individuals found along the search remain in the population. In elitist replacement, an elite set is defined which is constituted by the best individuals found so far. The number of descendants generated is less than the size of the population. Descendants replace individuals in the population that are not part of the elite set. The choice of the number of elite individuals is directly related to the selection pressure, that is, the higher this number the more influential elite individuals tend to be in the search process and the diversity of the population may tend to decrease.

3.3.1.8 Diversity

A key feature for the proper functioning of an evolutionary approach is the existence of diversity between individuals of the population. The diversity of the population is a measure associated with differentiation of solutions in the space of solutions. If the individuals are very similar, diversity is low and the crossover operator has no ability to exchange useful information among individuals, thus making the progress of the search very slow or even the population to stagnate. If diversity is high, the possibility of escaping from just local optima increases because it is possible to explore more comprehensively the search space. Typically, a larger population shows greater diversity, but the computational effort to control a big population may be prohibitive.

3.3.1.9 Stop Criteria

The condition to stop the search process may be associated either to the point of evolution reached (i.e. quality of solutions already computed) or to the computational effort measured in execution time of the algorithm.

According to Eiben and Smith [228], generally the end of the search process occurs when it hits one or more of the following conditions:

- Maximum number of generations;
- No significant improvement of the solutions for a number of consecutive generations;
- Minimum value for the standard deviation of the fitness value of the solutions in the population;
- Maximum CPU time;
- Minimum limit of population diversity;
- A "good solution" has been obtained, if it is possible to make this assessment.

3.3.2 Differential Evolution - Based Approach

In this section, the Differential Evolution (DE) algorithm to solve optimization problems is presented, which was proposed in 1995 by Storn and Price [229]. DE is characterized by using a simple mutation operator based on the difference between vectors, that is, a pair of solutions, to find a search direction based on the solution distribution in the population.

DE has been attracting the attention of researchers from different areas of knowledge, as can be seen by the increasing number of publications originating DE-based variants [229–232].

The algorithm incorporates a mutation operator, which is applied after crossover with a certain probability, in order to add a small variation to the variables. Moreover, DE uses a scheme similar to a replacement tool, where the new generated offspring (trial vector) enters into competition with its matching parent (old object vector) and substitutes it if the offspring has greater fitness value. DE shares some characteristic with evolutionary approaches and also some differences [233]. The similarities are the following: DE is a population-based approach, recombination and mutation are the variation operators used to generate new solutions and a replacement mechanism provides capabilities to maintain a fixed size population. The self-adapting characteristic of differential mutation gives DE very interesting qualities regarding optimization such as robustness, versatility and efficiency.

Solutions in DE are generally encoded with real values but DE does not use a fixed distribution (as the Gaussian distribution adopted in Evolutionary Strategies) to control the behavior of the mutation operator; instead, the current distribution of solutions in the search space determines the step sizes and the search direction of each individual. This latter feature seems to be one of its main advantages [233].

A vector obtained by the difference of two randomly selected vectors is added to a third individual (base vector) also randomly selected, creating a new mutant solution:

$$\boldsymbol{v_{t,i}} = \boldsymbol{x_{t,r_1}} + \boldsymbol{F}\left(\boldsymbol{x_{t,r_2}} - \boldsymbol{x_{t,r_3}}\right), \quad \boldsymbol{r_1}, \boldsymbol{r_2}, \boldsymbol{r_3} \in \{\boldsymbol{1}, \ldots, \boldsymbol{NP}\} \tag{4.3}$$

Where ***F*** is a scale factor applied to the difference vector and *NP* is the population size.

This procedure is used to obtain a mutant population ***V_t = {$v_{t,I;}$ i= 1,…,NP}.*** Then the population individuals ***X_t*** are recombined with individuals of the mutant population producing test solutions ***U_t*.**

3.3.2.1 Differential Evolution Variants

There are some variants of the DE algorithm. The notation is defined by DE/x/y/z, where ***x*** denotes the donor vector, ***y*** denotes the number of different vectors used, and ***z*** represents the crossover method.

The most popular variant is called "*DE/rand/1/bin*", where "*rand*" indicates that the donor vector is chosen at random, "1" is the number of pairs of solutions chosen (often at random) to calculate the differential mutation and "bin" means that a binomial recombination is used.

The corresponding algorithm of this variant is presented in:

DE/rand/1/bin" algorithm pseudocode:

G=0
Create a random initial population $x_{i,G}$ $\forall i, i = 1, \ldots, NP$
While a stopping criteria is not met **Do**
  For *i*=1 to NP Do
    Select randomly $r_1, r_2, r_3 \in \{1, 2, \ldots, \mathrm{NP}\}$
    $j_{rand} := randint(1, D)$
    For j=1 to D **Do**
      If ($rand_j[0,1] < CR$ or $j = j_{rand}$) **Then**
        $u_{i,j,G+1} := x_{r3,j,G} + F(x_{r1,j,G} - x_{r2,j,G})$
      Else
        $u_{i,j,G+1} := x_{i,j,G}$
      End If
    End for
End for
For *i*=1 to NP Do
  If ($f\left(u_{i,G+1}\right) \leq f\ (x_{i,G})$) **Then**
    $x_{i,G+1} := u_{i,G+1}$
  Else

$x_{i,G+1} := x_{i,G}$
End If
End for
G=G+1
End while

Where:

Randint (min, max) is a function that returns an integer number between min and max.

"rand" [0,1] is a function that returns a real number between 0 and 1.

Both are based on a uniform probability distribution.

NP is population dimension.

"MAX_GEN" is the maximum number of generations.

"D" number of variables.

"CR" [0,1] is a parameter that controls the number of values of $\boldsymbol{u_{i,j,G+1}}$ that are copied from the mutation vector. As close to 1 the C value is, the higher is the chance that the new solution contains values from the mutation vector.

F is a scalar factor applied to the difference vector that determines the influence of the pairs of solutions selected to compute the mutation value (one pair in the case of the DE/rand/1/bin algorithm) [234].

Figure 13 illustrates the DE mutation and recombination operator in its most popular variant (DE/rand/1/bin). In Figure 13, $\boldsymbol{x_{r_3}}$ is the donor individual chosen at random (but it can be the best solution in the population in other variants), $\boldsymbol{x_{r_1}}$ and $\boldsymbol{x_{r_2}}$ are the individuals chosen at random to compute the difference vector in order to define a search direction. The black circles represents the mutation vector, which can be the location of the only offspring generated after performing recombination. Additionally, the filled squares are the other two possible locations for the only offspring after recombination

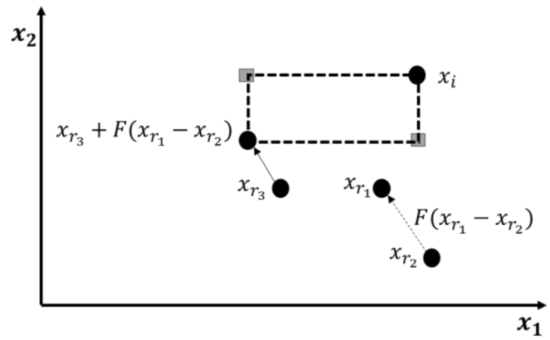

Figure 13 – Example of DE/rand/1/bin recombination and mutation operators [235].

As it was mentioned, the difference among the DE variants lies mostly on the technique the donor solution (from the pair chosen to compute the "mutation vector") is selected, the number of pairs of randomly chosen solutions and the type of recombination operator adopted. The main variants are [234]:

<u>Variants with discrete recombination operator (either binomial or exponential):</u>

- DE/rand/1/bin
- DE/rand/1/exp
- DE/best/1/bin
- DE/best/1/exp

The "rand" variants select the donor solution ($\boldsymbol{x}_{\boldsymbol{r}_3}$) and the pair of solutions to calculate the differential mutation ($\boldsymbol{x}_{\boldsymbol{r}_1}$and $\boldsymbol{x}_{\boldsymbol{r}_2}$) at random. In contrast, the "best" variants use the best solution in the population as the donor solution and the pair of solutions is chosen at random.

<u>Variants with arithmetic recombination:</u>

- DE/ current-to-rand/ 1
- DE/ current-to-best/1

The only difference between these variants is that the first one selects the donor solution ($\boldsymbol{x}_{\boldsymbol{r}_3}$) and the pair of solutions to calculate the differential mutation ($\boldsymbol{x}_{\boldsymbol{r}_1}$ and $\boldsymbol{x}_{\boldsymbol{r}_2}$) at random. The second one uses the best solution in the population as the donor solution.

Variants with combined arithmetic discrete recombination:

- DE/ current-to-rand/ 1/bin

The implementation details of each DE variation are summarized in

Table 4 , where perturbations of the donor vector by the mutation operator are presented.

Table 4 - DE basic variants [235]

Variant
Rand/p/bin:
$u_{i,j} = \begin{cases} x_{r_3,j} + F.\sum_{k=1}^{p}\left(x_{r_1^p,j} - x_{r_2^p,j}\right) & from\ U_j(0,1) < CR\ or\ j = j_r \\ x_{i,j} & otherwise \end{cases}$
Rand/p/exp:
$u_{i,j} = \begin{cases} x_{r_3,j} + F.\sum_{k=1}^{p}\left(x_{r_1^p,j} - x_{r_2^p,j}\right) & from\ U_j(0,1) < CR\ or\ j = j_r \\ x_{i,j} & otherwise \end{cases}$
Best/p/bin:
$u_{i,j} = \begin{cases} x_{best,j} + F.\sum_{k=1}^{p}\left(x_{r_1^p,j} - x_{r_2^p,j}\right) & from\ U_j(0,1) < CR\ or\ j = j_r \\ x_{i,j} & otherwise \end{cases}$
Best/p/exp:
$u_{i,j} = \begin{cases} x_{best,j} + F.\sum_{k=1}^{p}\left(x_{r_1^p,j} - x_{r_2^p,j}\right) & from\ U_j(0,1) < CR\ or\ j = j_r \\ x_{i,j} & otherwise \end{cases}$
Current-to-rand/p:
$u_i = x_i + K.(x_{r3} - x_i) + F.\sum_{k=1}^{p}\left(x_{r_1^p} - x_{r_2^p}\right)$
Current-to-best/p:
$u_i = x_i + K.(x_{best} - x_i) + F.\sum_{k=1}^{p}\left(x_{r_1^p} - x_{r_2^p}\right)$
Current-to-rand/p/bin:
$u_{i,j} = \begin{cases} x_{i,j} + K.\left(x_{r3,j} - x_{i,j}\right) + F.\sum_{k=1}^{p}\left(x_{r_1^p,j} - x_{r_2^p,j}\right) & if\ \ U_j(0,1) < CR\ \ or\ \ j = j_r \\ x_{i,j} & otherwise \end{cases}$

j_r is a random integer number generated in the interval [0,n], where ***n*** is the number of variables of the problem. ***Uj (0,1)*** is a real number generated at random between 0 and 1. Both numbers are generated using a uniform distribution. $\boldsymbol{p}$ is the number of pairs of solutions used to calculate the differences in the mutation operator. $\boldsymbol{u_i}$ is the offspring (or trial vector), $\boldsymbol{x_{r3}}$ is the donor solution chosen at random, $\boldsymbol{x_{best}}$ is the best solution in the population as donor solution, $\boldsymbol{x_i}$ is the current parent (old object vector) and $\boldsymbol{x_{r1}^p}$ and $\boldsymbol{x_{r2}^p}$ are the $\boldsymbol{p^{th}}$ pair to compute the differential mutation.

3.4 Evolutionary MOO Approaches

In the first applications of EA to solve MOO problems in practice, mostly weighted-sum approaches were used [236,237]. Goldberg [213] suggested the use of the dominance relation to sort individuals in a population. In the Multi-Objective GA (MOGA) [238], all individuals are assigned a rank depending on how many solutions dominate a specific solution. The selection procedure then chooses lower rank solutions to form the mating pool. Since the fitness of an individual is its rank, many population members have the same fitness. MOGA then uses a niching procedure to promote diversity in the population.

The Niched-Pareto GA (NPGA) utilized a Pareto dominance tournament [239]. In this technique, a comparison set comprising a specific number of individuals is randomly chosen from the population at the beginning of the selection procedure. An individual is then randomly chosen from the population, being compared with a member of the comparison set for dominance assessment. The non-dominated individual is selected; if none individual dominates the other, the individual presenting the lower value of niche counting is selected to ensure a certain distance between individuals in the decision variable space.

Elite-preserving operators favour the best individuals in the population by giving them the opportunity to be directly carried over to the next generation. In general, elitism improves convergence to the global optimal solution, in single objective problems, or to the Pareto optimal front, in MOO problems, because the preservation of very good solutions enhances the probability of creating better offspring. Although the presence of elitism can contribute to improve the performance of a MOO EA, it may also cause loss of diversity. The balance between the convergence to the Pareto front and solution diversity requires a controlled elitism in MOO with EA. The Non-dominated Sorting GA II (NSGA) is presently the most well-known EA devoted to MOO [240]. Other examples of elitist approaches are the Strength Pareto EA (SPEA) [241] and SPEA 2 [242].

3.4.1 Non-elitist approaches

3.4.1.1 Vector Evaluated Genetic Algorithm (VEGA)

VEGA was the first approach of a GA for calculating non-dominated solutions to a MOO problem [243]. The population at any generation is divided into ***NP/M*** subpopulations, where ***M*** is the number of objectives and ***NP*** is the population size. A fitness value based on the corresponding objective function only is assigned to each individual in each subpopulation. The selection procedure emphasizes good solutions for each objective function. The crossover operator between two good solutions, each corresponding to a different objective, is used to generate offspring that are good compromise solutions.

The proposed approach differs from a standard GA in the way fitness is assigned to each solution in the population. The rest of the algorithm (using stochastic universal selection, single point crossover, and bit-wise mutation) is the same as that in a classical GA. In order to maintain diversity among non-dominated solutions, niching among solutions in each rank is introduced. Despite each solution is evaluated only for an objective function during the process of selection, which in general impairs reaching good convergence to Pareto optimal solutions, this algorithm is a reference for its simplicity and because it pioneered the implementation of GA to deal with MOO problems.

3.4.1.2 Weight-based Genetic Algorithm (WBGA)

The WBGA was introduced by Hajela and Lin [244]. In this algorithm each objective function $f_m(x)$ is multiplied by a weight w_m (m = 1, ..., M). Every individual consists not only of the decision variables, but also their associated weights. The fitness values of individuals in the population are determined using a weighted-sum method in each iteration, leading to several non-dominated solutions corresponding to various combinations of weights.

3.4.1.3 Multiple Objective Genetic Algorithm (MOGA)

Fonseca and Fleming [238] proposed MOGA, which was the first approach to explicitly use the concept of non-dominance and simultaneously preserve the diversity of population. The main feature of MOGA lies on how fitness is assigned to each solution. The classification of a particular individual in the population is proportional to the number of individuals it dominates. MOGA uses stochastic universal selection, one-point crossover and simple binary mutation. In order to ensure diversity in the population, Fonseca and Fleming [238] introduced a strategy based on a niche scheme between solutions with the same classification.

3.4.1.4 Non-dominated Sorting EA (NSGA)

The classification of the solutions by levels of dominance proposed by Goldberg [213] was implemented in its entirety by Deb and Srinivas [245], in an approach called Non-dominated Sorting GA (NSGA). As MOGA, this algorithm also uses selection based on the dominance concept to rank the solutions. In this algorithm, there is a mechanism to distribute solutions in levels of dominance and other to preserve the diversity among solutions in each non-dominated front. The fitness assignment process starts from the initial non-dominated set and consecutively goes to dominated sets. A solution $\boldsymbol{i}$ of the first non-dominated set is assigned a fitness value $\boldsymbol{F_i = NP}$, where $\boldsymbol{NP}$ is the population size. In order to promote diversity, the sharing function method is used, which degrades the fitness value based on the number of neighboring solutions. A sharing function is calculated based on the distance between solutions. After the computation of the sharing function values, the niche count of each solution is calculated, which denotes the number of solutions in its neighborhood. The procedure of debasing the fitness of a solution highlights solutions in less crowded regions of the search space. This procedure completes the fitness assignment procedure of all solutions in the first front. Thereafter, a fitness value slightly smaller than the minimum shared fitness in the first front is assigned to solutions in the second non-dominated front, guaranteeing that solutions in the first front present a shared fitness better than the solutions in the second front. Finally, the assigned shared fitness is used to select the mating pool and genetic operators are applied to produce a new population. The other genetic operators, crossover and mutation, are used in the usual way on the entire population.

3.4.1.5 Niched-Pareto EA (NPGA)

The Niched-Pareto GA (NPGA) was proposed by Horn [239], differing from the previous approaches essentially in the type of selection mechanism. Unlike other approaches (VEGA, NSGA and MOGA) applying the proportional fitness selection, NPGA combines the technique of sharing fitness value with a mechanism by tournament selection.

The algorithms mentioned in this section do not use any strategy of maintenance in the population of the best individuals found in the search. There are, however, several mechanisms to protect these solutions, which are used in approaches classified as elitist.

3.4.2 Elitist approaches

The non-elitist MOO EA do not implement explicit mechanisms to preserve the best individuals in the evolutionary process. The “second generation” MOO EA implement elite-preserving operators in different ways, such as NSGA-II [246], Strength Pareto EA (SPEA) [242], Pareto-archived ES (PAES) [247], and others. Algorithms with elitist behavior ensure that the best individuals are kept in the population, avoiding the possible degradation of the population performance.

Unlike what happens in single-objective EA, incorporating elitism in MOEA may not be trivial. In the case of MOO problems, in general, a set of candidate (non-dominated) solutions exists in every generation and therefore it must be decided which and how solutions are selected. Simply choosing all non-dominated solutions is not the most appropriate in situations where there are many solutions in these circumstances.

Several mechanisms have been developed to implement elitism, although the most common is maintaining an external population with (a selection of) non-dominated individuals in the current generation. The way this population of elected individuals influences the main population varies from algorithm to algorithm.

Here were only refer to three MOEA with elitist behavior (SPEA, NSGA II and SPEA 2), which are the ones most reported in the literature, with a large number of applications.

3.4.2.1 Strength Pareto EA (SPEA)

The Strength Pareto Evolutionary Algorithm (SPEA) was proposed in [241] as an elitist multi-objective EA based on non-dominance. An external population is maintained, keeping the non-dominated solutions that are obtained in each generation. The selection process uses a combination of the degree to which a candidate solution is dominated (strength) and an estimation of density of the non-dominated front to assign the fitness. Solutions that dominate more solutions have a better fitness.

3.4.2.2 Strength Pareto EA 2 (SPEA 2)

An improved version of SPEA was presented in [242], which was called SPEA 2.

The main differences of SPEA 2 with respect to SPEA are:

1. The mechanism to determine the fitness of a given solution uses a strategy based on the number of solutions that dominate it and the number of solutions that are dominated by it.
2. The mechanism incorporates an additional technique to estimate the density of non-dominated solutions in a given search space region, in order to discriminate solutions with similar characteristics in terms of the non-dominance relation.
3. A method is applied to the external population to preserve the best extreme solutions in this population (solutions with the best values for each objective function).
4. Only solutions in the external population participate in the selection process.
5. A modified clustering algorithm is used based on the k-th nearest neighbors distance estimates for each cluster [248].
6. As the size of the external population is constant, it can also contain dominated solutions.

3.4.2.3 Elitist Non-dominated Sorting EA (NSGA - II)

The Non-dominated Sorting GA II (NSGA II) is presently the most well-known EA devoted to MOO [240]. It diverges from MOGA in fitness assignment and the technique used to compute the niching. The Elitist Non-dominated Sorting Genetic Algorithm (NSGA-II) was presented in [246,249], which uses not just an elite-preserving strategy but also an explicit diversity-preserving mechanism.

NSGA II implements an efficient procedure for introducing elitism into an MOO EA while also promoting diversity. In NSGA II, in generation (iteration) t, the offspring population E_t is created by using the parent population D_t both of size NP. However, instead of finding the non-dominated front of E_t only, first the two populations are combined together to form a population R_t of size 2NP. This population is classified with a non-dominated sorting algorithm. Although this requires more effort compared with performing a non-dominated sorting on E_t alone, it allows a non-dominance check among offspring and parent solutions. Then the new population is filled by solutions of different non-dominated fronts, one at a time. The process begins with the best non-dominated front and proceeds with solutions of the second non-dominated front (that is, the non-dominated front after the solutions of the first front have been removed), and so on. Since the size of R_t is 2NP, not all fronts can be accommodated in the NP slots available in the new population. When the last front is being considered, there may be more solutions in the last front than the remaining slots in the new population. Instead of arbitrarily discarding some members from the last front, a niching strategy is used to choose the members of the last front that reside in the least crowded region in that front. This scheme is illustrated in Figure 14.

Initially, a random population D_0 is created. The population is sorted into different non-dominance levels. Each solution is assigned a fitness equal to its non-dominance level (1 will be assigned to the first non-dominated front). Accordingly, it will be assumed the minimization of the fitness. Binary tournament selection, recombination and mutation operators are used to create an offspring population E_0, of size N. The stopping criterion is the number of generations (iterations).

Step 1 Combine parent and offspring populations to create $R_t = D_t \cup E_t$. Perform a non-dominated sorting in R_t and identify different fronts F_i, $i = 1, 2, ...$.

Step 2 Set a new population $D_{t+1} := \emptyset$. Set counter i=1.

While $|D_{t+1}|+|F_i| < N$, do $D_{t+1} := D_{t+1} \cup F_i$ and $i := i+1$.

Step 3 Perform the Crowding-sort ($F_i < c$) procedure (mentioned below) and include the most widely spread solutions into D_{t+1}, by using the crowded distance values in the sorted F_i.

Step 4 Create an offspring population E_{t+1} from D_{t+1} by using the binary crowding tournament selection, crossover and mutation operators.

The process of non-dominated sorting and filling the population D_{t+1} steps can be performed together, so that every time a non-dominated front is found its size can be used to check if it can be included in D_{t+1}. If this is not possible, no more sorting is needed.

In Step 3, the crowding-sorting of the solutions in front F_i, which is the last front that could not be completely accommodated, is performed by using a crowded-distance. The crowding comparison operator compares two solutions and returns the winner of the tournament. The winner is selected based on two attributes: the non-dominance ranking r_i and the local crowding distance d_i, in the population. This crowding distance attribute of a solution i is a measure of the search space around i, which is not occupied by any other solution in the population. d_i is an estimate of the perimeter of the cuboid formed by using the nearest neighbours as the vertices (which is called the crowding distance; Figure 15). Based on r_i and d_i the binary crowding tournament selection operator works as follows - a solution *i* wins a tournament over another solution *j* if any of the following conditions are true:

1. If $r_i < r_j$ (this makes sure that the solution chosen lies on a better non-dominated front).
2. If $r_i = r_j$ and $d_i > d_j$ (this is applied when both solutions lie on the same front and the condition above cannot be applied; in this case the solution residing in a less crowded area, with a larger d_i, wins).

A detailed explanation of NSGA II can be found in [246,249].

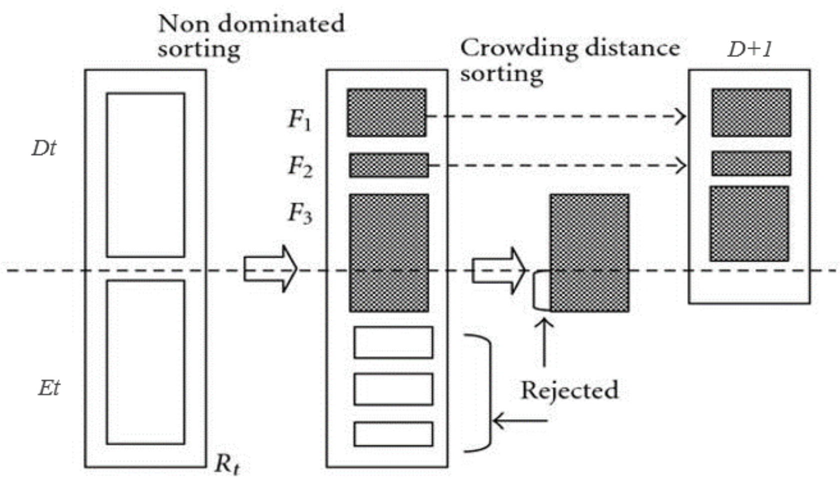

Figure 14 - Schematic operation of the NSGA-II procedure [250]

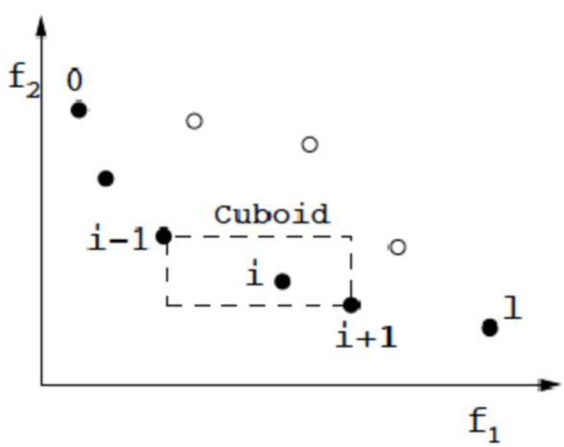

Figure 15 - The crowded distance calculation [235]

3.4.2.4 Non-dominated Sorting Differential Evolution (NSDE)

The Non-dominated Sorting Differential Evolution (NSDE) was proposed in [251], which is based on NSGA-II, with small modifications as presented in [246]. The crossover and mutation operators in NSGA-II are replaced in NSDE by the DE operators. Novel individuals are generated using the DE/current-to-rand/1/variant.

3.5 CONCLUDING REMARKS

This chapter briefly presented the characteristics of some MOEA that have gained a large acceptance in the scientific community. These evolutionary approaches have shown to be of great utility in solving complex MOO problems due to their adaptive nature to the particularities of the problems.

In most complex MOO problems, the presence of conflicting and incommensurable objectives generally leads to a very high number of non-dominated solutions. EAs working with solution populations overcome the problem of calculating only one solution at each iteration (as in scalarizing approaches), inspecting the search space faster and more effectively.

4. Chapter 4 - A Multi-objective Model for the energy Box Aggregator

The aim of this chapter is to develop a model representing a framework for the EBAg role in the electric power system. This comprises the information that is transmitted from an LEB to the EBAg and the relationships between the LEB and the SO.

The large-scale deployment of LEB imposes an essential challenge concerning the coordination of grid and end-user objectives. I.e., requests from the grid should be weighed against end-user flexibility to shift or shed loads. In this setting, the EBAg will gather flexibility from the end-users associated with it by means of LEB, requiring them to adjust their daily load profile, using a remuneration scheme specified in a contract with end-users associated in clusters. A critical issue is the incentive paid to the end-users to participate in these demand management programs and provide load operation flexibility in a cost effective way for all stakeholders.

Thereby, the EBAg is able to sell the flexibility gathered from consumer clusters and presenting offers to the grid, according to its requests, in the form of ancillary services, with the aim of offering benefits to all entities involved (increasing retail profits, decreasing consumption costs). The EBAg will be able to receive signals from the SO and take appropriate actions to avoid violation of grid operational constraints. For instance, in case of abnormal operating conditions, the SO can request the EBAg load increasing or decreasing, in each time slot. The interaction with the SO may be also important for solving congestions in the distribution grid.

4.1 MOO model for the EBAg

The MOO model includes two objective functions:

F1 (economic function) - the aim is to maximize the EBAg profits, taking into account the remuneration for selling the load flexibility obtained from the end-user clusters to the SO, the rewards paid to each cluster, the penalties paid to the SO for not meeting the flexibility requests and the sanctions applied to each cluster for the amount of flexibility compromised with the cluster and not made available.

The load flexibility provided by each cluster is considered as uncertain since the end-user can decide to use loads that were previously committed as available; in this way the cluster is considered as not entirely reliable and therefore a range of reliability applies, i.e. a degree of reliability associated with each cluster is generated within a certain pre-defined range or even for each time slot.

F2 (Fairness function) – the aim is to minimize the inequity (imbalance) among clusters, i.e., minimizing the maximum relative difference between the load flexibility offered by the clusters and the one actually used by the EBAg, as a surrogate for fairness in the usage of end-user load flexibility.

The data used in mathematical models are frequently uncertain [252], since data often result from assumptions done based on the context of the problem, prediction and forecast of occurrences, measurements subject to errors, etc. In our case, we used some real data from audits, gathered from 50 end-users 24/7 during one year, which were useful to obtain a realistic sample, although with some dimension and representativeness limitations.

Indices

c = 1,2, …C – Identify the cluster, where ***C*** is the number of clusters associated with the EBAg. Each cluster gathers a set of end-users (LEB).

t = 1,2,…T – Identify the time slot, considering a time resolution of 15 minutes (T=96 time slots in one day).

Coefficients

I^{+}_{t} - Reward paid by the SO to the EBAg for the flexibility provided (load decrease, i.e., power decrease), in each time slot ***t***.

I^{-}_{t} - Reward paid by the SO to the EBAg for the flexibility provided (load increase), in each time slot ***t***.

E^{+}_{t} - Reward paid by the EBAg to the clusters (equal for all clusters) for the flexibility used (load shedding, i.e. effective load decreased), in each time slot *t*, according to the EBAg requests.

E^{-}_{t} - Reward paid by the EBAg to the clusters (equal for all clusters) for the flexibility used (load increase), in each time slot ***t***.

F^+_t - Penalty paid by the EBAg to the SO for not complying with the contracted flexibility (load shedding, i.e., power decrease), in each time slot t.

F^-_t - Penalty paid by the EBAg to the SO for not complying with the contracted flexibility (load increase), in each time slot t.

C^+_{ct} - Penalty applied by the EBAg to the cluster c for the amount of flexibility not used (load decrease), in each time slot t.

C^-_{ct} - Penalty applied by the EBAg to the cluster c for the amount of flexibility not used (load increase), in each time slot t.

R^+_t – Power reduction (load shedding/shifting) requested by the SO to the EBAg, in each time slot t.

R^-_t – Power increase requested by the SO to the EBAg, in each time slot t.

$D_{max}{}^+{}_{ct}$ - Maximum value of power that cluster c can offer to the EBAg (decrease) in each time slot t.

$D_{max}{}^-{}_{ct}$ - Maximum value of power that cluster c can offer to the EBAg (increase) in each time slot t.

∂^+_c - Minimum fraction of $D_{max}{}^+{}_{ct}$ that cluster c may offer to decrease load (positive flexibility margin).

∂^-_c - Minimum fraction of $D_{max}{}^-{}_{ct}$ that cluster c may offer to increase load (negative flexibility margin).

D^+_{ct} – Amount of power that cluster c can to decrease, in each time slot t, accounting for a range of variation in the cluster response.

D^-_{ct} – Amount of power that cluster c can to increase, in each time slot t, accounting for a range of variation in the cluster response.

$$D^+_{ct} = \mathrm{rand}(\partial^+_c, 1)\, D_{max}{}^+{}_{ct}$$

$$D^-_{ct} = \mathrm{rand}(\partial^-_c, 1)\, D_{max}{}^-{}_{ct}$$

In this way, D^+_{ct} and D^-_{ct} account for the uncertainty associated with the flexibility effectively provided by end-user clusters.

Decision variables

P^+_t – Amount of power (kW) that the EBAg offers to the SO, in each time slot t, corresponding to load shedding/shifting (power decrease).

P^-_t – Amount of power (kW) that the EBAg offers to the SO, in each time slot t, corresponding to power increase.

$$P^+_t . P^-_t = 0$$

L^+_{ct} – Amount of power that the EBAg uses from cluster c corresponding to power decrease (load shedding/shifting) in each time slot t.

L^-_{ct} – Amount of power that the EBAg uses from cluster c corresponding to power to increase in each time slot t.

$$L^+_{ct} . L^-_{ct} = 0$$

Objective functions

Maximizing the EBAg profits, taking into account the revenues of selling the load flexibility obtained from the end-user clusters to the grid and the rewards given to the clusters as well as the penalties paid to the grid for not meeting the flexibility requested and to the clusters for flexibility made available and not used:

$$\max z_1 = \sum_t I_t^+ P_t^+ + \sum_t I_t^- P_t^- - \sum_t \sum_c E_t^+ L_{ct}^+ - \sum_t \sum_c E_t^- L_{ct}^- - \sum_t F_t^+ (R_t^+ - P_t^+) - \sum_t F_t^- (R_t^- - P_t^-)$$
$$- \sum_t \sum_c C_t^+ (D_{ct}^+ - L_{ct}^+) - \sum_t \sum_c C_t^- (D_{ct}^- - L_{ct}^-)$$

Minimizing inequity among clusters, i.e., minimizing the maximum relative difference between the load flexibility provided by the clusters and the one used by the EBAg:

$$\min z_2 = \max_c \sum_t (L_{ct} - D_{ct}) / D_{ct}$$

Constraints

The amount of power that the EBAg uses from cluster c to decrease/increase cannot be higher than the amount of power to decrease/increase offered by cluster c in time slot t:

$$L^{+}_{ct} \leq D^{+}_{ct}\text{ , } \textit{for all c,t}$$

$$L^{-}_{ct} \leq D^{-}_{ct}\text{ , } \textit{for all c,t}$$

The amount of power that the EBAg offers to the grid to decrease/increase cannot be higher than the amount of power required to decrease/increase in each time slot ***t***:

$$0 \leq P^{+}_{t} \leq R^{+}_{t}\text{ , } \textit{for all t}$$

$$0 \leq P^{-}_{t} \leq R^{-}_{t}\text{, } \textit{for all t}$$

The amount of power that the EBAg offers to the grid to decrease/increase shall not be higher than the total amount of power used to decrease/increase from what is offered by the clusters in time slot ***t***:

$$0 \leq P_t^{+} \leq \sum_c \sum_t L_{ct}^{+}$$

$$\leq P_t^{-} \leq \sum_c \sum_t L_{ct}^{-}$$

4.2 Case Study

Experiments have been done based on real data collected using the Cloogy device (www.cloogy.pt) during one year, January 2013 to January 2014, of continuous (24/7) monitoring of electrical energy consumption with a time resolution of 15 minutes. These data provided a realistic basis for the specification of clusters, energy prices, baseline load profiles and load flexibility offered by each cluster.

Cloogy is an HEMS for the residential sector, based on a fully interactive ICT infrastructure, which allows the end-user to monitor global and individual consumption and control electrical appliances, helping them to optimize the use of electricity by appliances and reduce the energy bill. Cloogy was developed be ISA – Intelligent Sensing Anywhere, S.A. with the aim to be an easy plug and play solution that any homeowner can quickly install. The global architecture of the solution can be seen in Figure 16 and the technical specifications in Figure 17.

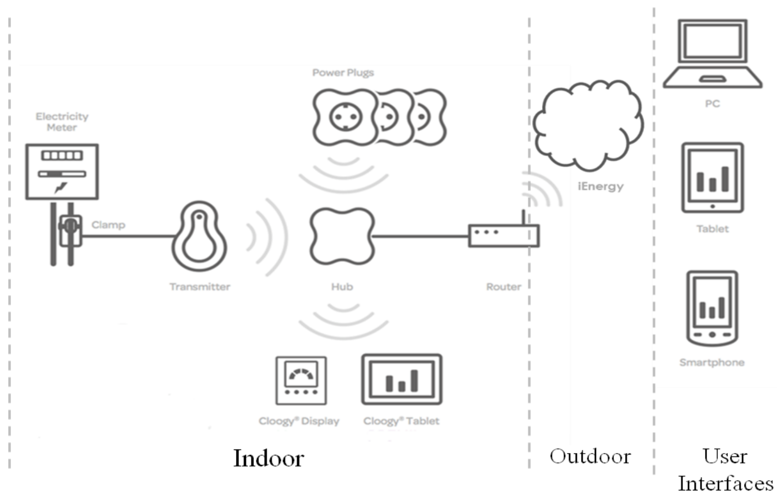

Figure 16 - Cloogy Global Architecture [33]

Features	Hub	Power Plug	Transmitter	Cloogy® Display
Weight without batteries	94,9g / 0.20lb	112g / 0.24lb	69,4g / 0.15lb	253,4g / 0.55lb
Size	L: 90mm / 3.543in; W: 90mm / 3.543in; H: 33mm / 1.299in	L: 80mm / 3.15in; W: 80mm / 3.15in; H: 45mm / 1.77in; Total H: 82mm / 3.22in	L: 113mm / 4.44in; W: 75mm / 2.95in; H: 27mm / 1.06in	L: 108mm / 4.25in; W: 100mm / 3.93in H: 113mm / 4.44in
Beacon interval	–	On demand Adaptable Every 5s Every 30s	On demand Adaptable Every 5s Every 30s	–
Standby Consumption (W)	1,2 (<1,5)	0,73 (<1)	–	0,5 (Powered at 230V)
Power Supply	230V	230V	Batteries 3xAA	230V or Batteries 3xAA
Battery Autonomy	–	–	240 days	365 days
Measured / Shown Data	–	Electric current Voltage Frequency Electric Power Energy Power factor	Electric Current Battery level	Energy Spent Money Spent (Current and previous) Current Time Temperature Battery Level (Sent to the Hub)
Maximum electric current	–	16A	50A	–
Maximum Voltage	–	400V	–	–
Electric current measurement accuracy	–	±3%	±3%	–
Connection	2,4GHz (Zigbee)			
Interfaces	Ethernet RF Zigbee LED RGB	RF Zigbee LED RGB	Switch: forces a conection to the hub RF Zigbee LED	4 touch keys RF Zigbee LCD com 69mmx60mm Removable plastic front
Range	–	20-30m / 65-98ft with barriers	40-50m / 131-164ft with barriers	20-30m / 65-98ft with barriers

Figure 17 - Cloogy Technical Specifications[33]

The sample was composed of 30 end-users in the region of Coimbra and 20 in the region of Lisbon, in Portugal, with 18 250 daily load diagrams analyzed.

A selection of 9 000 daily load diagrams was used. These load diagrams were aggregated into clusters, i.e. groups of end-users with similar features of their electricity consumption profile based on their consumption average and load factor (ratio average load/peak load in a specific time period), as can be seen in Figure 18. The cluster A includes the end-users with a load factor between 0-5% and the cluster T contain the clients with load factor of 95-100% (Table 5).

The EBAg requires information about the response of each cluster to the request signals. Since this may be uncertain there is a confidence parameter associated with each cluster to take into account human factors and variability of energy consumption behaviors. Each cluster indicates to the EBAg its load flexibility margin for each time slot, reflecting the cluster availability to reduce/increase the load thus changing the load profile. This information derives from historical data. The positive and negative load flexibility margins are displayed from Figure 28 to Figure 36, which means that the clusters are able to reduce and increase their load, respectively.

These flexibility margins were assumed according to previous work of categorization of the load in households. Although some studies [253–255] indicate that with the use of HEMS it is possible to reduce 30% of consumption, we have adopted more conservative values with a maximum of consumption deviation of 12.5% and only in the cluster presenting a load factor between 40% and 60%.

Table 5 - Clusters: load factor, load flexibility range

Cluster	Load Factor	Flexibility range	Cluster	Load Factor	Flexibility range
A	0-5%	0-2.5%	M	60-65%	7.5-10%
(...)	(...)	(...)	N	65-70%	7.5-10%
I	40-45%	10-12.5%	O	70-75%	5-7.5%
J	45-50%	10-12.5%	P	75-80%	5-7.5%
K	50-55%	10-12.5%	(...)	(...)	(...)
L	55-60%	10-12.5%	T	95-100%	0-2.5%

Eight clusters were created based on the analysis of the 9 000 daily load diagrams. The baseline load profile is displayed in Figure 18.

To obtain the amount of flexibility for each cluster throughout the planning period, this flexibility margin is applied to its load profile. For instance, when the cluster load factor is 45% and the consumption is higher than the average consumption, then it is possible to have load shedding (i.e., decrease in the load) up to 12.5% (positive flexibility); when the consumption is lower than the average consumption it is possible to have an increase of up to 10% (negative flexibility). The flexibility margin is applied to the baseline load profile in each time-slot to obtain the amount of load flexibility, with some uncertainty.

The revenues received by the EBAg from the grid and rewards given to the EBAg to the cluster are based on the electricity tariffs, but considering significant variations (in frequency and amplitude) along the day in some way mimicking the wholesale electricity market.

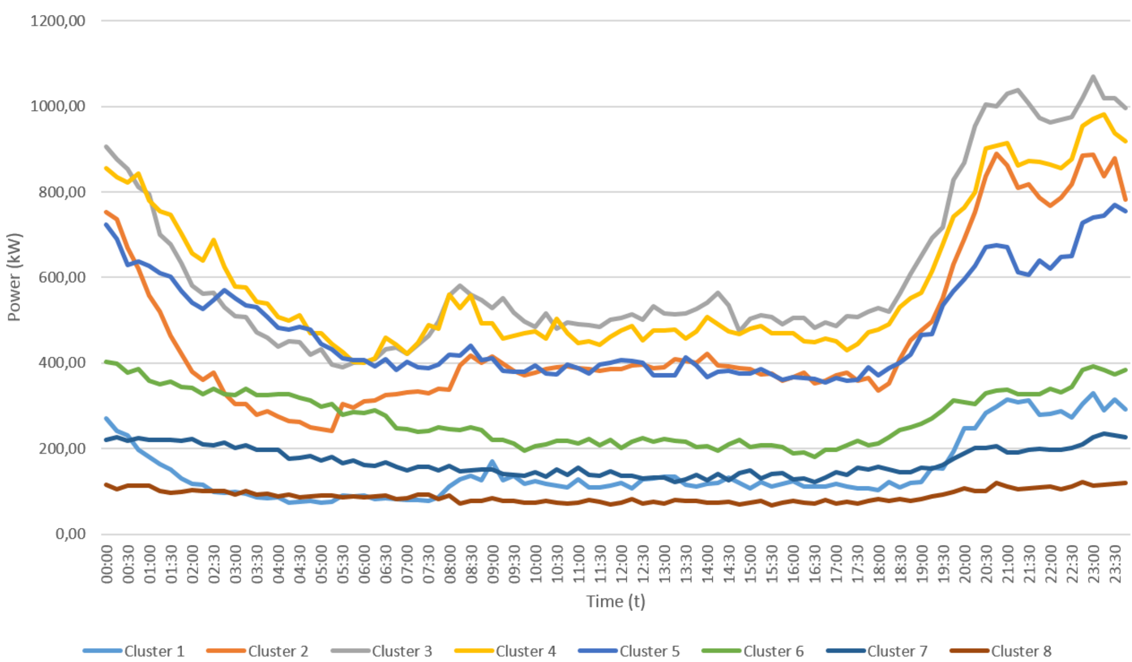

Figure 18 - Baseline load diagram of each cluster

Figure 18 displays the baseline energy consumption of each cluster with an average aggregate power of 2 739 kW/day (sum of all clusters) and a total energy consumption of 65 742 kWh during one day.

Cluster 1 is composed of 865 load diagrams with load factor of 28% (Figure 19), average power 148.25 kW, total consumption 3 558 kWh during one day; the maximum power is 329.96 kW and the minimum power is 74 kW.

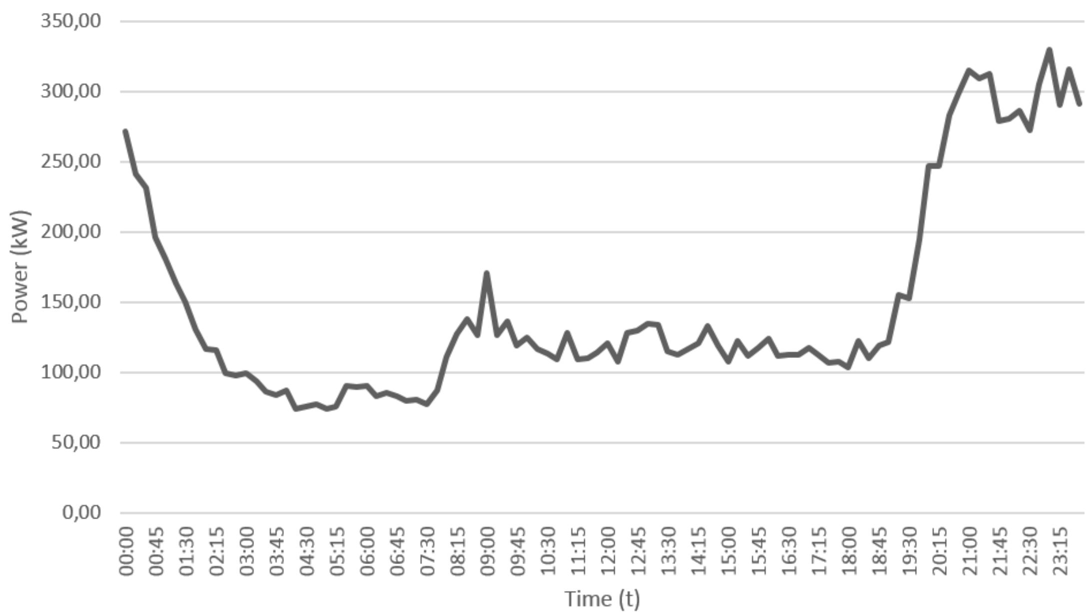

Figure 19 - Baseline Energy Consumption of Cluster 1.

Cluster 2 is composed of 800 load diagrams with load factor 45% (Figure 20), average power 461.57 kW, total consumption 11 078 kWh during one day; the maximum power is 889.84 kW and the minimum power is 241.96 kW.

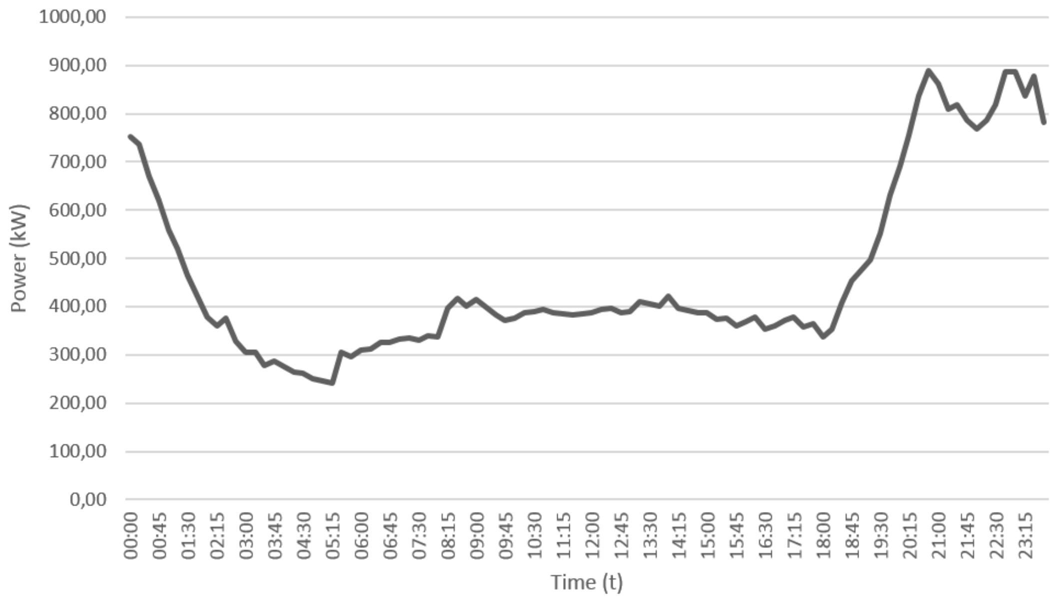

Figure 20 - Baseline Energy Consumption of Cluster 2.

Cluster 3 is composed of 1 780 load diagrams with load factor 52% (Figure 21), average power 613.47 kW, total consumption 14 723.22 kWh during one day, the maximum power is 1 068.87 kW and the minimum power is 389.57 kW.

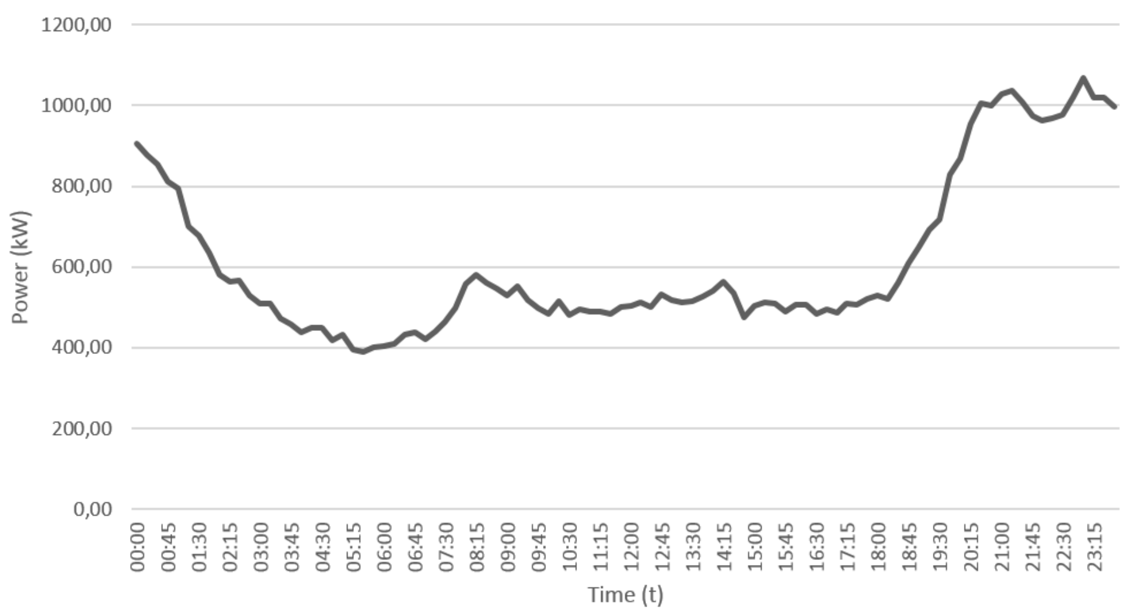

Figure 21 - Baseline Energy Consumption of Cluster 3.

Cluster 4 is composed of 1 485 load diagrams with load factor 60% (Figure 22), average power 586.98 kW, total consumption 14 087.55 kWh during one day, the maximum power is 980.44 kW and the minimum power of 400.32 kW.

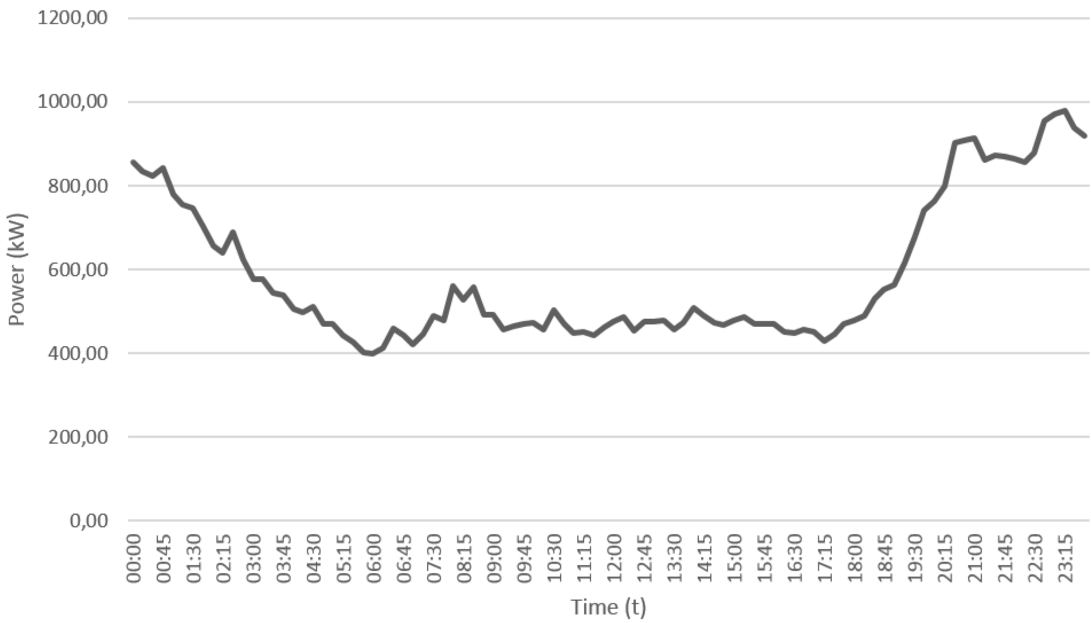

Figure 22 - Baseline Energy Consumption of Cluster 4

Cluster 5 is composed of 1 069 load diagrams with load factor 62% (Figure 23), average power 478.83 kW, total consumption 11 491.99 kWh during one day, the maximum power is 770.69 kW and the minimum power of 354.34 kW.

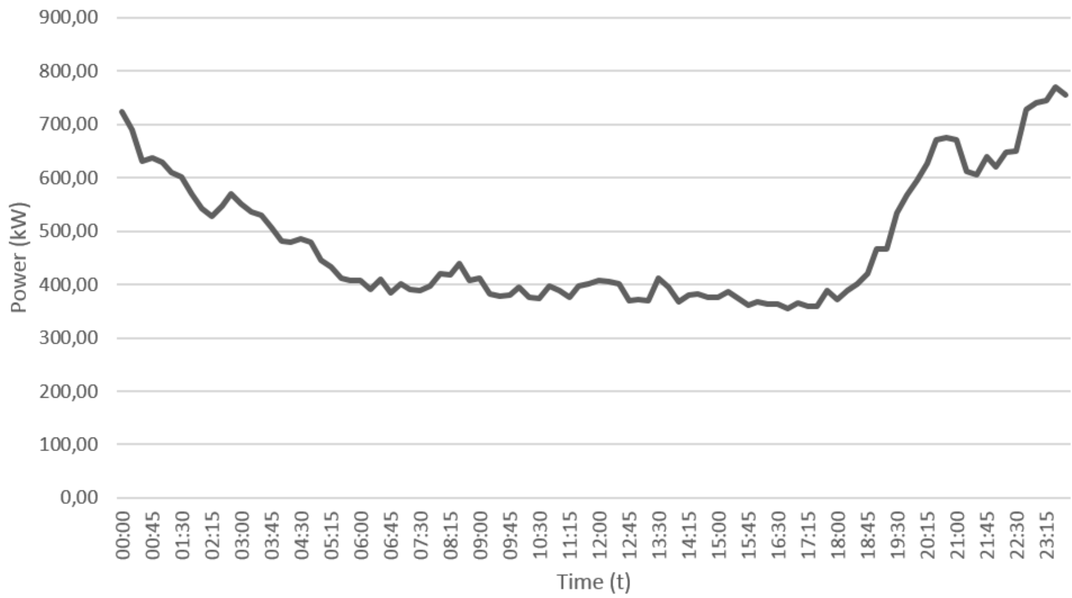

Figure 23 - Baseline Energy Consumption of Cluster 5

Cluster 6 is composed of 651 load diagrams with load factor of 68% (Figure 24), average power 273.74 kW, total consumption 6 569.77 kWh during one day, the maximum power is 403.08 kW and the minimum power is 179.91 kW.

Figure 24 - Baseline Energy Consumption of Cluster 6

Cluster 7 is composed of 387 load diagrams with load factor 72% (Figure 25), average power 169.25 kW, total consumption 4 062.08 kWh during one day, the maximum power is 234.90 kW and the minimum power is 121.59 kW.

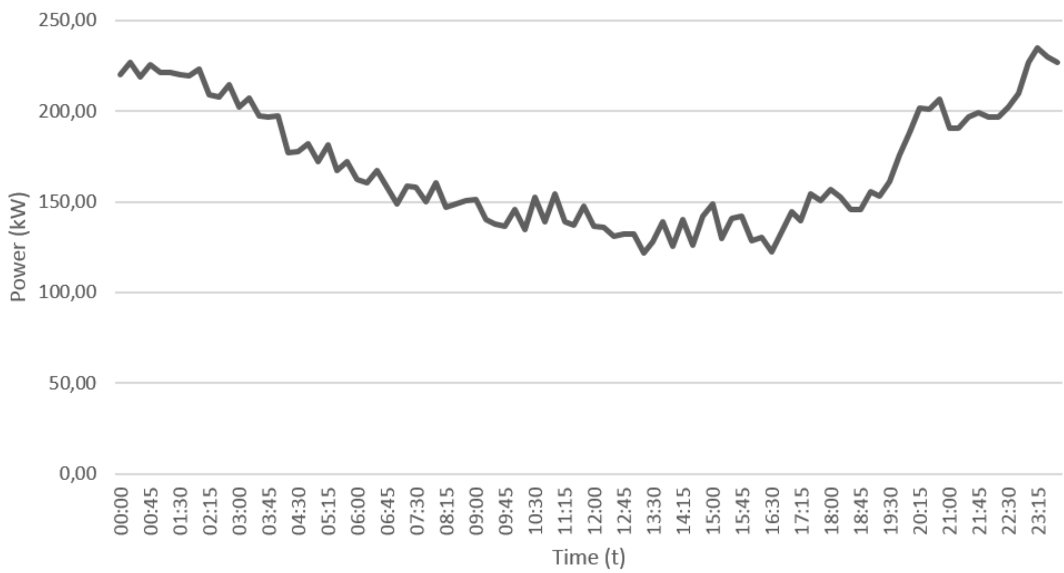

Figure 25 - Baseline Energy Consumption of Cluster 7

Cluster 8 is composed of 1 953 load diagrams with a load factor 88% (Figure 26), average power 82.12 kW, total consumption 2 139 kWh during one day, the maximum power is 121.73 kW and the minimum power is 68.63 kW.

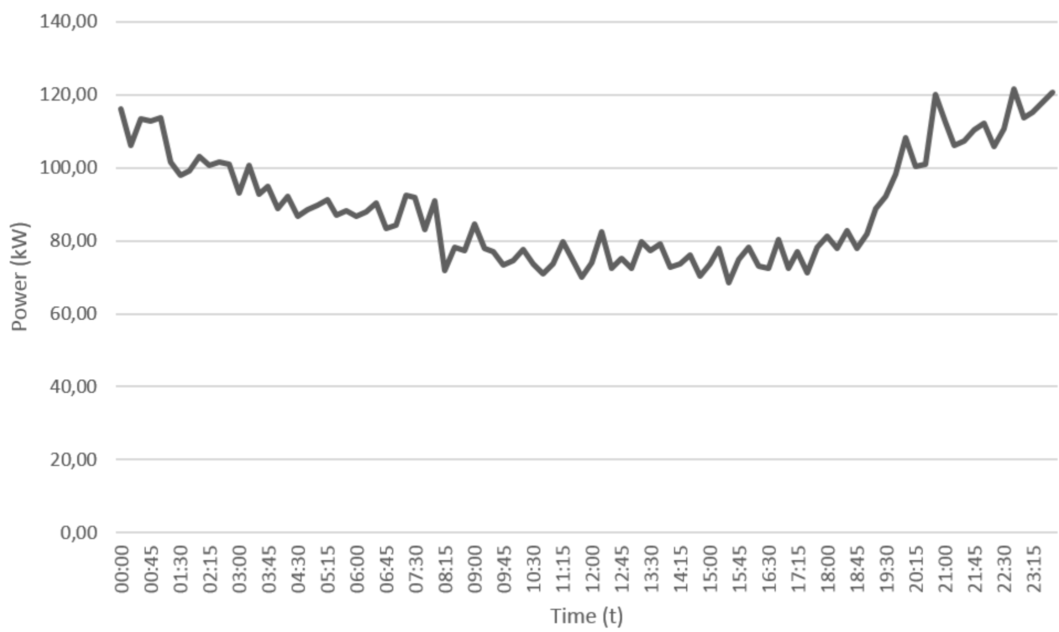

Figure 26 - Baseline Energy Consumption of Cluster 8

The data to feed the coefficients of the MOO model are presented below. Figure 27 displays the requests ($\boldsymbol{R^{+}_{t}}$ and $\boldsymbol{R^{-}_{t}}$) of the SO to the EBAg.

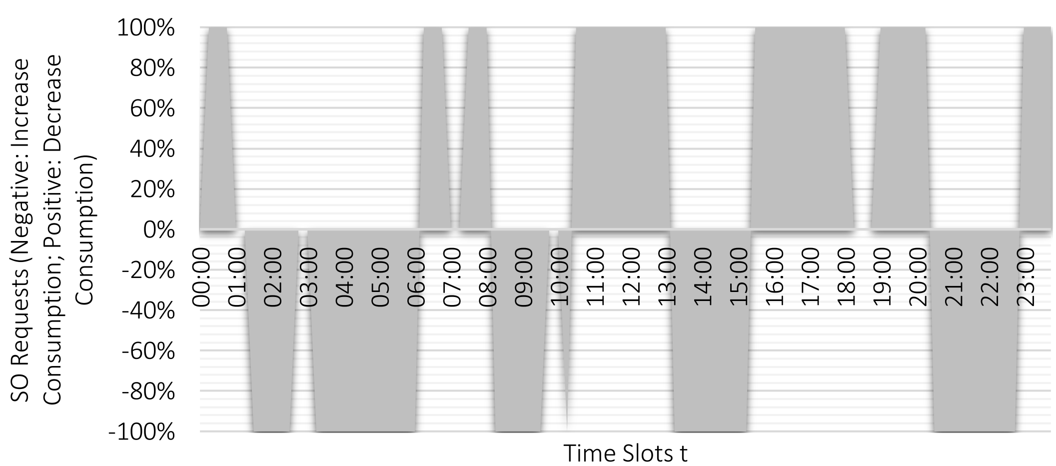

Figure 27 - SO requests to the EBAg

Figure 28 to Figure 37 present the maximum value of power that each cluster can decrease ($\boldsymbol{D_{max}{}^{+}{}_{ct}}$) or increase ($\boldsymbol{D_{max}{}^{-}{}_{ct}}$) in each time slot.

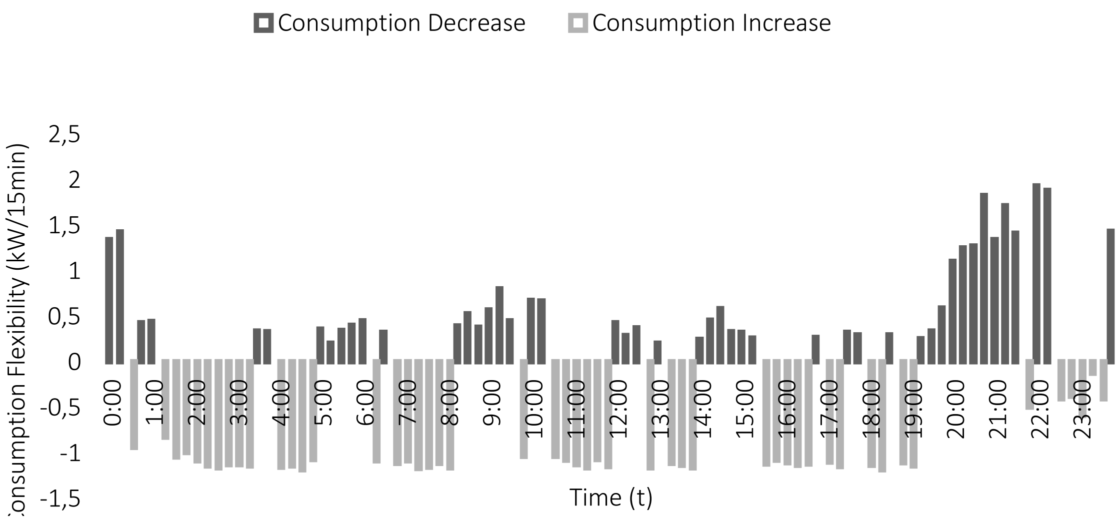

Figure 28 - Positive and Negative flexibility of cluster 1

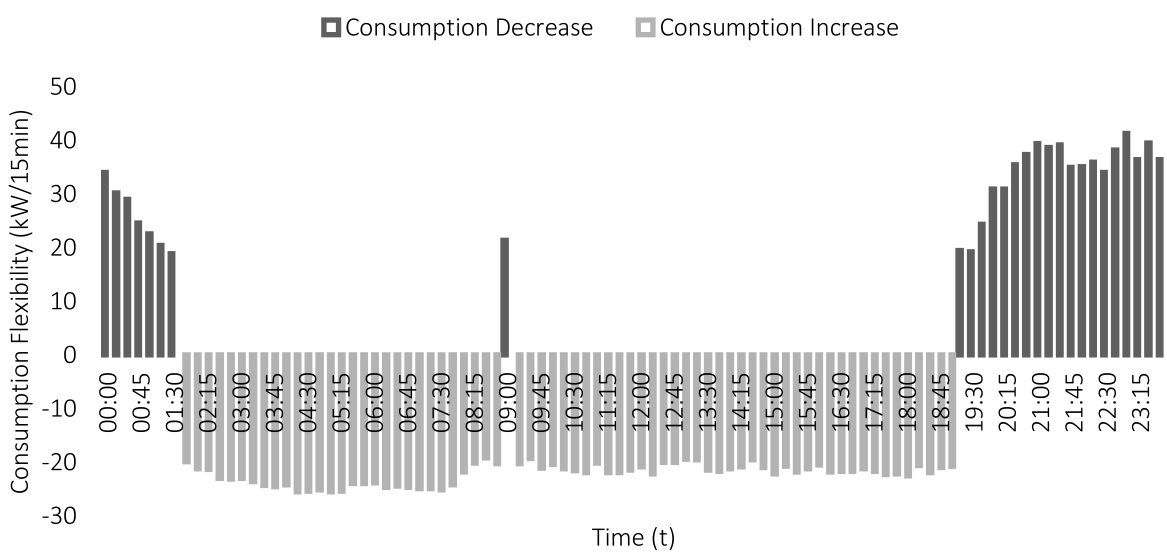

Figure 29 - Positive and negative flexibility of cluster 2

Figure 30 - Positive and Negative flexibility of cluster 3

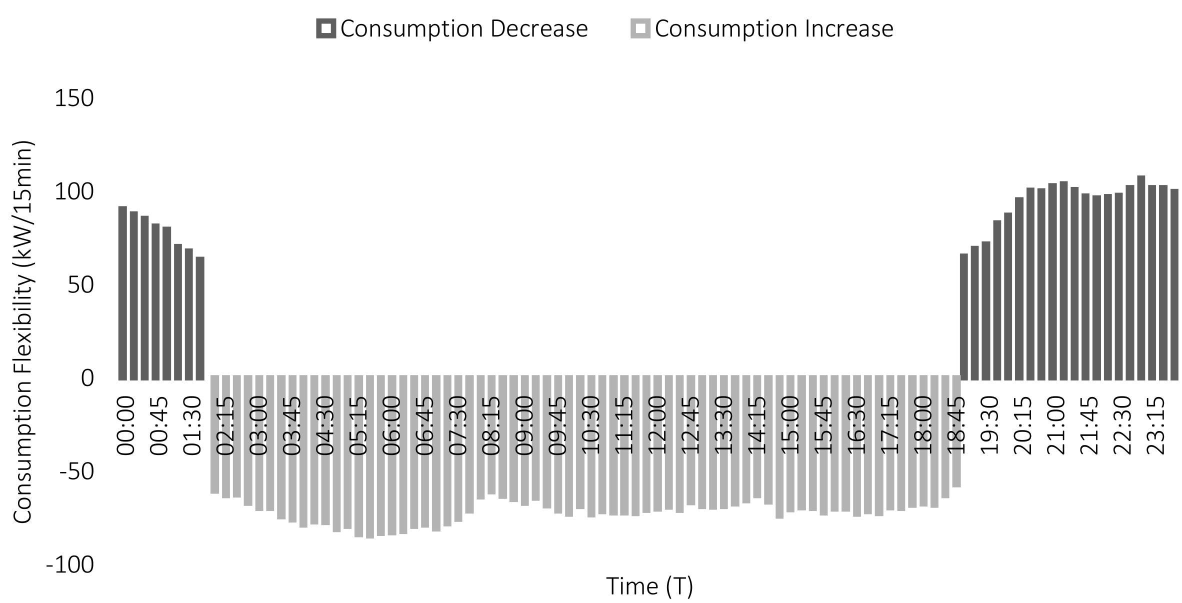

Figure 31 - Positive and Negative Flexibility of cluster 4

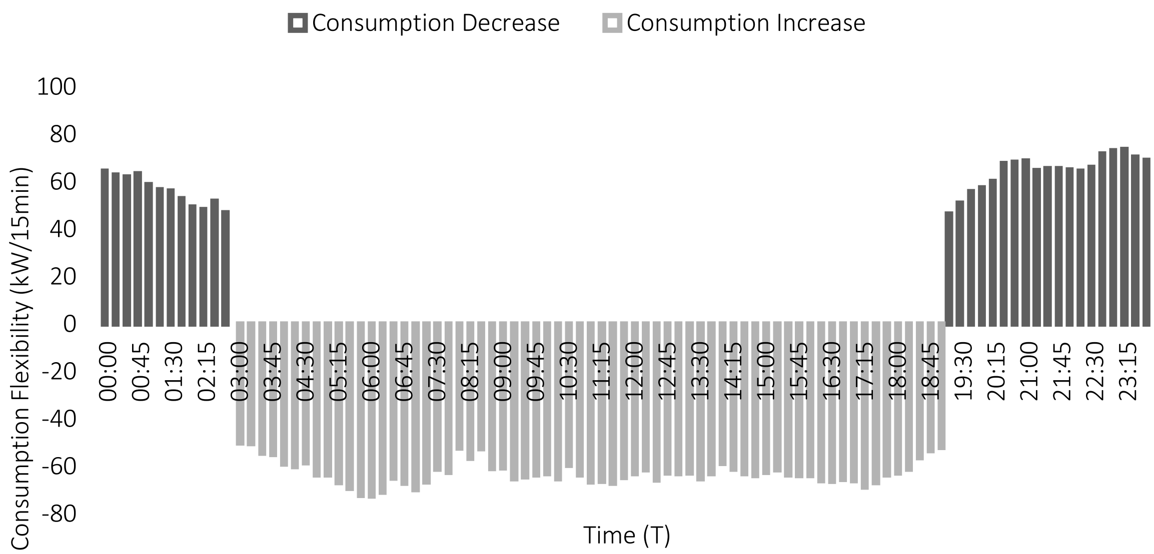

Figure 32 - Positive and Negative Flexibility of cluster 5

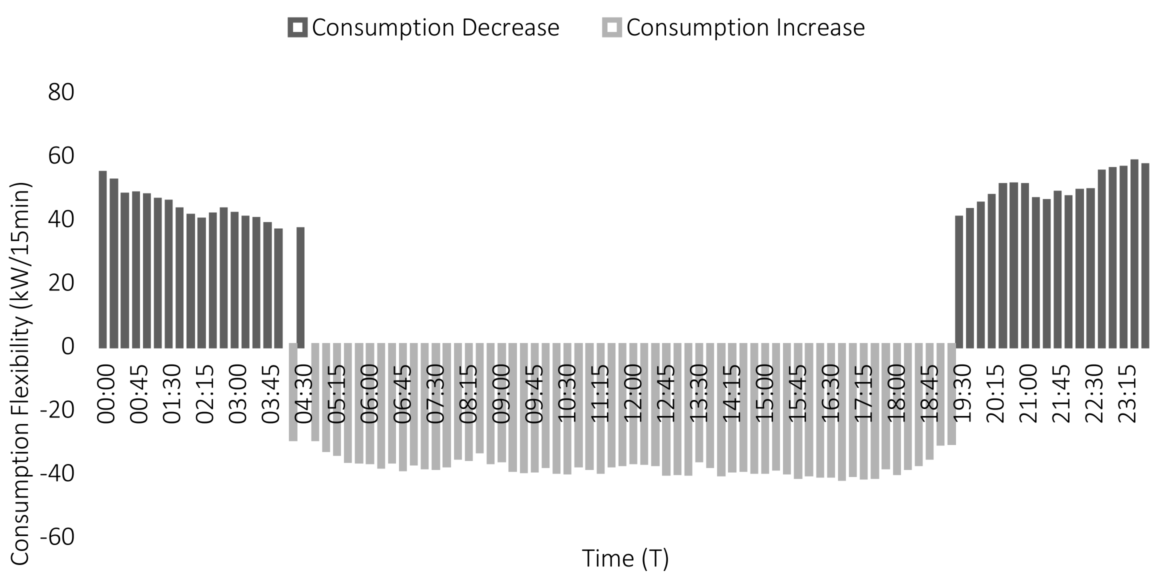

Figure 33 - Positive and Negative Flexibility of cluster 6

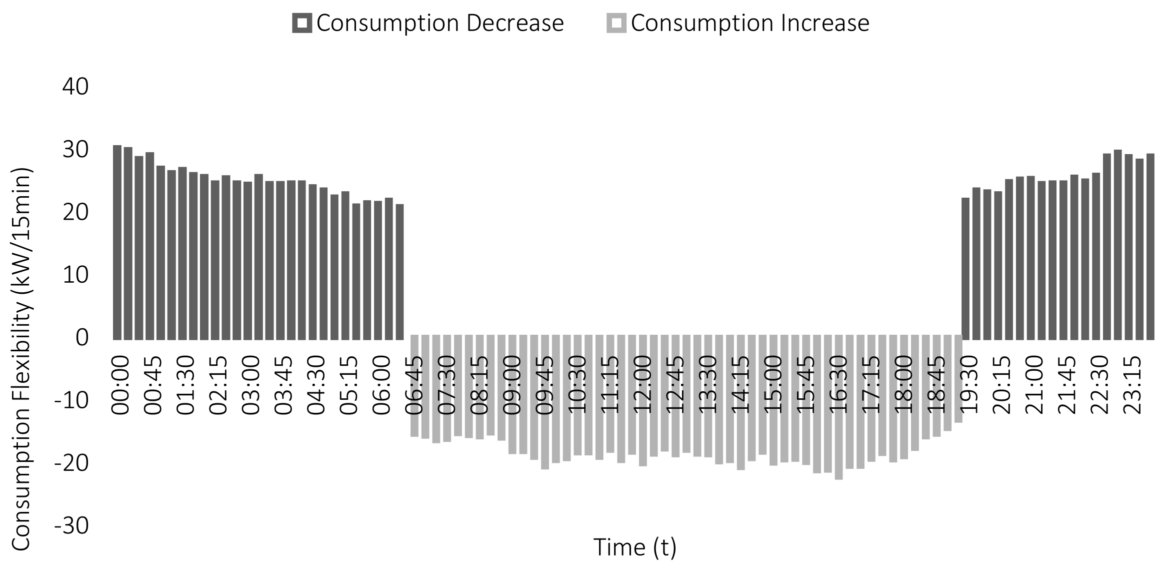

Figure 34 - Positive and Negative Flexibility of cluster 7

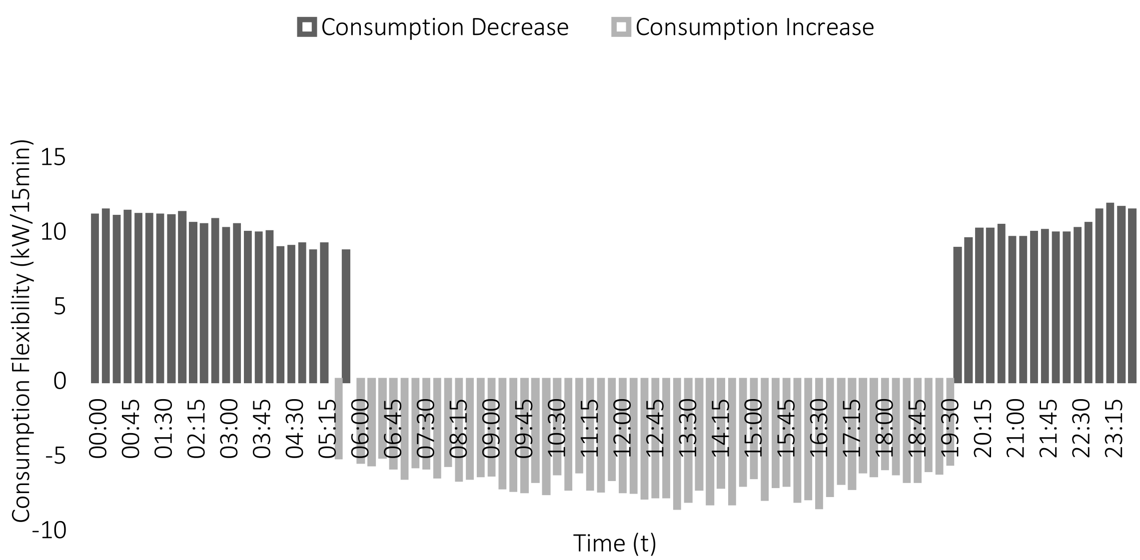

Figure 35 - Positive and Negative Flexibility of cluster 8

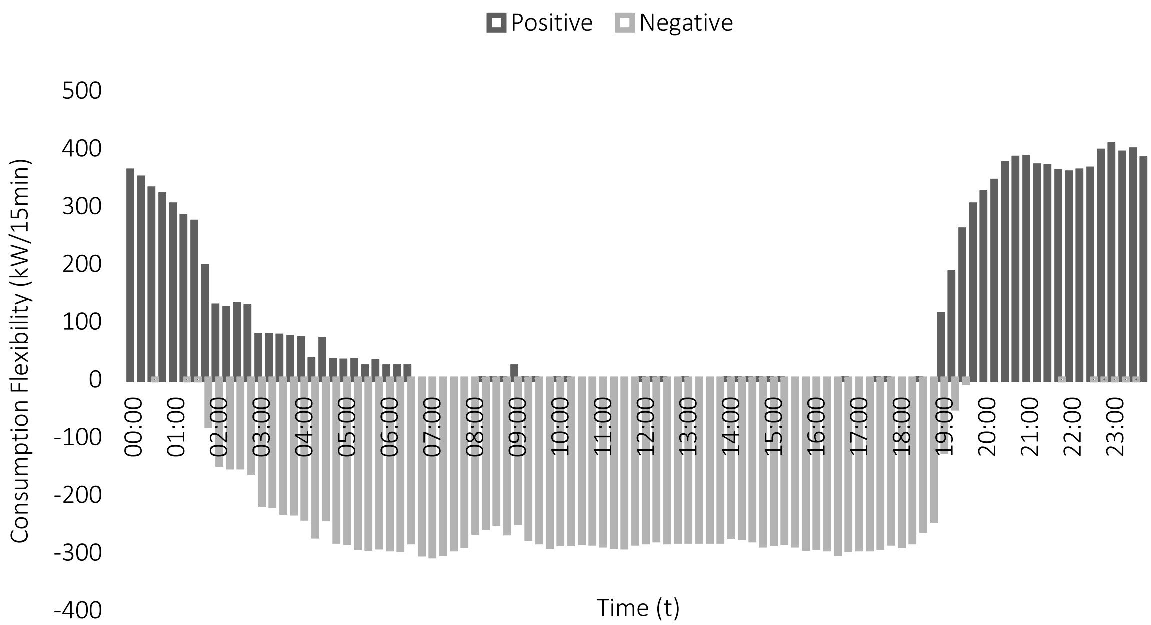

Figure 36 - Maximum Load Flexibility provided by all clusters to the EBAg.

Figure 37 presents the values of variation of the amount of power provided by all clusters (D^{+}_{ct}, D^{-}_{ct}), when they are subject to uncertainties of 5% and 10%.

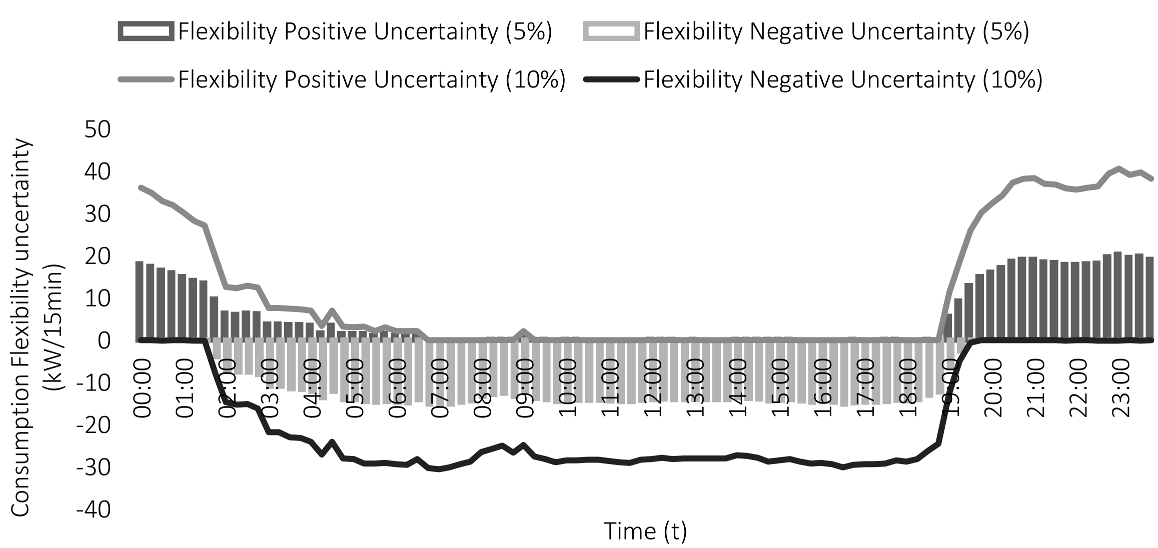

Figure 37 – Load Flexibility considering uncertainty from clusters

4.3 EBAg Business Model Canvas

The Business Model Canvas is a strategic management and entrepreneurial tool allowing to describe, design, challenge, and pivot a business model [256,257]. It is a visual chart with elements describing a firms or product's value, infrastructure, customers, and finances. The business model describes the rationale of how an organization creates, delivers, and captures value, in the economic, social, cultural or other contexts. The process of business model construction is part of the business strategy.

The term business model is used for a broad range of informal and formal description to represent core aspects of a business, including purpose, business process, target customers, offering strategies, infrastructure, organizational structures, trading practices, and operational processes and policies.

As a way to organize our concept of EBAg, we filled the business model canvas as displayed in Figure 38.

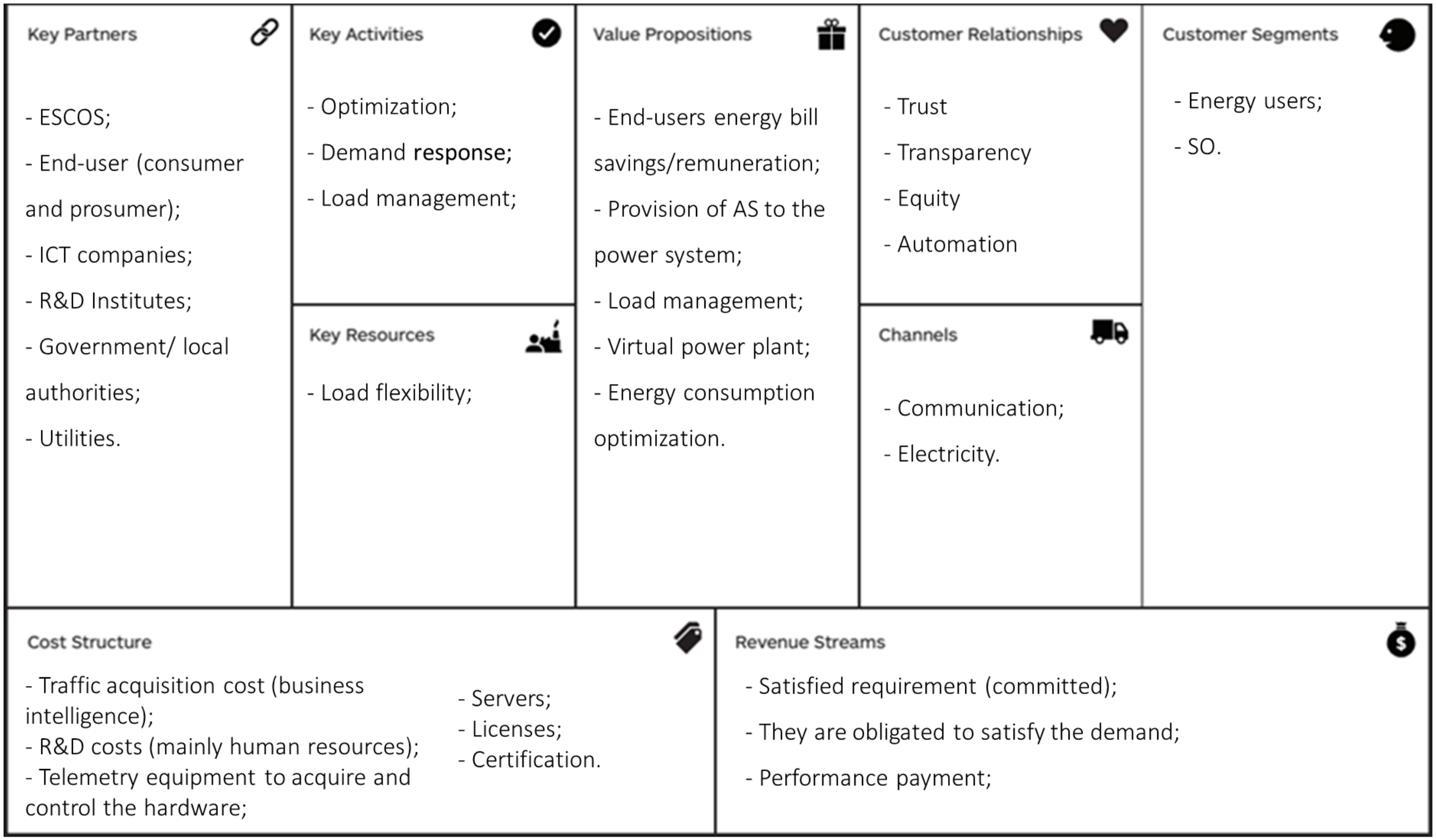

Figure 38 – Business Model Canvas [258]

Key Partners: The EBAg has as main partners the power system utilities, including retail companies selling electricity to end-users, as well as ESCOs, ICT companies, R&D institutes cooperating to improve EBAg computational intelligence aimed at enhancing profits and services provided. The EBAg business model is highly dependent of the government and regulatory authorities, which establish the legal/regulatory framework. Finally, yet importantly, the EBAg needs to offer attractive commercial proposals to end-users to exploit load flexibility and offer economic gains without jeopardizing the quality of the energy services provided (i.e. comfort or requiring engaging in very distinct energy behaviors and routines).

Key Activities: The EBAg key activity consists in balancing demand and supply enhancing a strategy of "demand follows supply" by giving incentives to end-users for their provision of load flexibility that will allow responding to grid requests and providing ancillary services. The EBAg will interact with HEMS (Home Energy Management System) able to control the appliances in the household from which the EBAg will gather the load flexibility, give economic rewards to end-users for their load availability / flexibility (load effectively managed) and apply a penalty to end-users for not complying with the load flexibility committed.

Key Resources: The key resource required by this value proposition is the knowledge about load flexibility from end-users.

Value Proposition: The EBAg is able to optimize the energy consumption in the residential sector, delivering advantages for the end-user, including economic incentives, better quality of service and potential reduction of energy bills. The optimization of residential consumption will be made also to satisfy power system requirements, including the provision of system services.

Customer Relationship: Cooperative relationship. The EBAg will use resources from the end-user to satisfy the SO requirements. Therefore, the EBAg will give economic incentives to end-users for the use of their loads, according to their preferences and constraints.

Channels: A communication infrastructure is needed to exchange information and for the successful implementation of a smart grid. The communication technologies (ex. ZigBee, WLAN, cellular, WiMAX, Power Line Communication, etc.) will allow an optimization of the smart grid coordination and will enable the coordination between the grid components from production to the HEMS to manage end-use loads.

Customer Segment: The customer segment consists of residential (and possibly small commerce/services) energy users and the SO as the entity of the power system responsible to ensure AS.

Cost Structure: The costliest item in the EBAg business model is the economic incentives to pay to the end-user for the load flexibility provided as well as penalties to pay the SO for not complying with the services previously committed.

Revenue Streams: End-users will not pay to benefit from the EBAg service (they may only receive economic benefits for changing consumption patterns according to EBAg requests). The EBAg receives revenues from the SO when it is able to commit with the flexibility previously agreed upon.

4.4 Concluding Remarks

This section presented a MOO model for the EBAg, which uses the load flexibility provided by each end-user to respond to the grid requests and facilitate a load follows supply strategy in a Smart Grid setting, with potential benefits for all participants involved. The role of the EBAg is twofold: it makes the most of demand responsive loads according to in-house load flexibility and it provides system services contributing to improve the system operation. The optimization model from the aggregator perspective presents multi-objective evaluation aspects (economic, quality of service, fairness) of the merits of potential solutions.

5. CHAPTER 5 – EBAg ALGORITHM IMPLEMENTATION, RESULTS AND DISCUSSION[5]

This chapter presents the implementation and analysis of results of the hybrid EA, which combines GA and DE. In this chapter, the process of obtaining the results is briefly described and illustrative results obtained from the model and algorithmic approach implemented are presented.

5.1 ALGORITHM IMPLEMENTATION AND ANALYSIS

The algorithmic approach has been designed to deal with the main characteristic of the EBAg model, namely its combinatorial nature, conflicting objective functions and uncertainty of the load flexibility provided by end-user clusters. Evolutionary algorithms are stochastic search and optimization methods that have proved very efficient and effective in dealing with combinatorial multi-objective models. Whereas (multi-objective) EA inspiration is from nature, i.e., where uncertainty is a communal occurrence, it cannot be assumed that these algorithms will be intrinsically robust to several sources of uncertainty [259]. To solve the model presented in Chapter 4 [194], an hybrid EA approach combining GA and DE was developed based on previous experience on solving problem with those characteristics, taking the advantages of both approaches, which are referred to in the literature as prominent approaches to solve MOO problems, specifically complex problems [260] [261] [262].

A non-dominated sorting genetic algorithm (NSGA-II) [246] coupled with a non-dominated sorting differential evolution algorithm (NSDE), which combines DE with the non-dominated selection procedure of NSGA-II [263–271], was developed to characterize the non-dominated front and explore the trade-offs between the conflicting objectives (maximizing the EBAg profits and minimizing the inequity among clusters). DE has revealed to be an efficient, effective and robust evolutionary optimization method, which has been applied in several studies [272–275] including in MOO problems [251,276–282]. DE differs from other EA essentially in the mutation and crossover operator; in DE the

[5] This chapter is partially based on Carreiro A.M., Oliveira C., Antunes C.H., Jorge H.M. (2015) An Energy Management System Aggregator Based on an Integrated Evolutionary and Differential Evolution Approach. In: Mora A., Squillero G. (eds) Applications of Evolutionary Computation. EvoApplications 2015. Lecture Notes in Computer Science, vol. 9028, 252-264. Springer, Cham.

perturbation mechanisms use weighted differences of decision space vectors to modify the population in subsequent iterations [262]. NSGA-II ranks solutions in terms of non-dominance levels, and provides each one with a crowding distance, which measures how much each individual contributes to diversity within a dominance rank, so being a measure of diversity of solutions in a given neighbourhood [246,271].

A hybrid evolutionary approach aimed at obtaining non-dominated fronts displaying a good spread and expected convergence to the Pareto optimal front (which is unknown) was developed, enabling to study the trade-offs between the two competing objective functions.

The hybrid algorithmic approach coupling EA and DE has the following main features:

1. Generation of the initial population – The initial population A_0 is created and sorted based on non-dominance, where each individual is assigned a fitness (rank) equal to its non-dominance level (where 1 is the best level, 2 the second-best level, and so on). The population is composed by NP=100 individuals generated based on the real data collected, as mentioned in section 4.2. For each time slot, a consumption value (kW) is randomly generated between -12% and 12% with respect to the load diagram baseline, ensuring that during one day (planning period) the total energy consumption can only change between -5% and 5% according to the load diagram baseline.
2. Generation of an offspring population – The offspring population B_0 is generated through tournament selection, crossover and mutation operators when using NSGA-II.
   2.1. When using EA: The crossover operator is executed with a probability 0.05 (NSGA-II). As the individual is composed of 4 real decision variables, where each consists of 96 time slots (resolution of 15 minutes), the crossover operator respects this structure, in the sense that each variable (physical) information is never broken. The mutation operator with a probability 0.05 works in each decision variable composing the individuals by randomly increasing/decreasing the amount of power within the range ±12% with respect to the load diagram baseline, while ensuring that during one day the total energy consumption can only change ±5%, also according to the measured baseline;
   2.2. When using DE: The mutant individuals are created using difference vectors based on the *DE/rand/1/bin* variant, since it consistently presented the best performance in comparison with other mutation strategies of the base vector [283]. The adoption of DE operators in the

multi-objective EA occurs when after 50 generations with NSGA-II, the values of the objective functions do not change.

3. A combined population $\boldsymbol{C_g} = \boldsymbol{A_g} \cup \boldsymbol{B_g}$ of size *2NP* (2x100) is formed, where $\boldsymbol{g}$ is the generation counter, ***g=1,…, G***;
4. Population $\boldsymbol{C_g}$ is sorted according to the non-dominance ranking procedure presented in [246] and hypervolume[6] calculation;
5. Population $\boldsymbol{A_{g+1}}$ of size *NP* is created using an elitist selection mechanism of the best solutions of $\boldsymbol{C_g}$. The process starts by the selection of the Pareto front of level 1, denoted $\boldsymbol{F_1}$. If $\boldsymbol{F_1}$ has a size smaller than ***NP***, then all solution of $\boldsymbol{F_1}$ stay in $\boldsymbol{A_{g+1}}$. The remaining members of the population $\boldsymbol{A_{g+1}}$ are chosen from subsequent non-dominated fronts $\boldsymbol{F_1}$, $\boldsymbol{F_2}$, … in the order of their ranking until $\boldsymbol{A_{g+1}}$ is composed by ***NP*** individuals. When just a few solutions need to be selected from a population, the crowding comparison operator is used. As larger is the crowding distance, the better the solution is since it is located in a less crowded region, as can be seen in Figure 39.
6. $\boldsymbol{B_{g+1}}$ is created from $\boldsymbol{A_{g+1}}$ using crossover and mutation operators;
7. This process continues until a stop condition is reached; in our case, the stop condition is verified when no evolution of the solutions is achieved after 50 generations. We assume that in these circumstances the convergence to the Pareto optimal front (which is unknown) is concluded.

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[6] The hypervolume indicator is a set measure used in evolutionary multiobjective optimization to evaluate the performance of search algorithms and to guide the search [324].

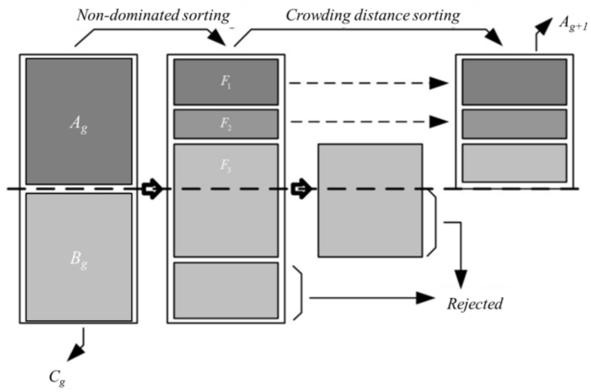


Figure 39 - NSGA-II and NSDE procedure of selection/elitism [250]

The diversity in non-dominated solutions is introduced by the crowding procedure, which is used in the tournament selection and during the population reduction phase. The parameters were tuned after extensive experimentation. Sets of 400 independent runs were carried out.

The main features of the solutions obtained using this hybrid algorithmic approach were:

- The EA consistently provided good extreme solutions for both objective functions, although displaying just a few solutions in the non-dominated front. The EA component was able to rapidly find good extreme solutions for both objective functions, namely regarding the profit objective function. The front then evolved in an intermittent manner with groups of (slightly) dominated solutions being outperformed by, in general, a single non-dominated solution. Then, the final non-dominated front was well spread (in the sense of good individual optimal solutions) but irregularly filled (few solutions in the front) in comparison to NSDE (see Figure 40, as an illustrative example).
- The DE component provided a well-spread and well-populated non-dominated front in a significant number of runs, but with major defaulting in the achievement of good extreme solutions and always less good in comparison to NSGA-II. The evolution of the front was quite regular. However, in a non-negligible number of runs the front was of low quality because no positive values of the profit objective function could be obtained. NSDE presented a better evolution regarding NSGA-II solutions when the initial population was not created randomly but rather using feasible solutions only.

The hybrid approach allowed a rapid convergence taking advantage of the best features of each multi-objective stochastic optimizer (see Figure 40 as an illustrative example).

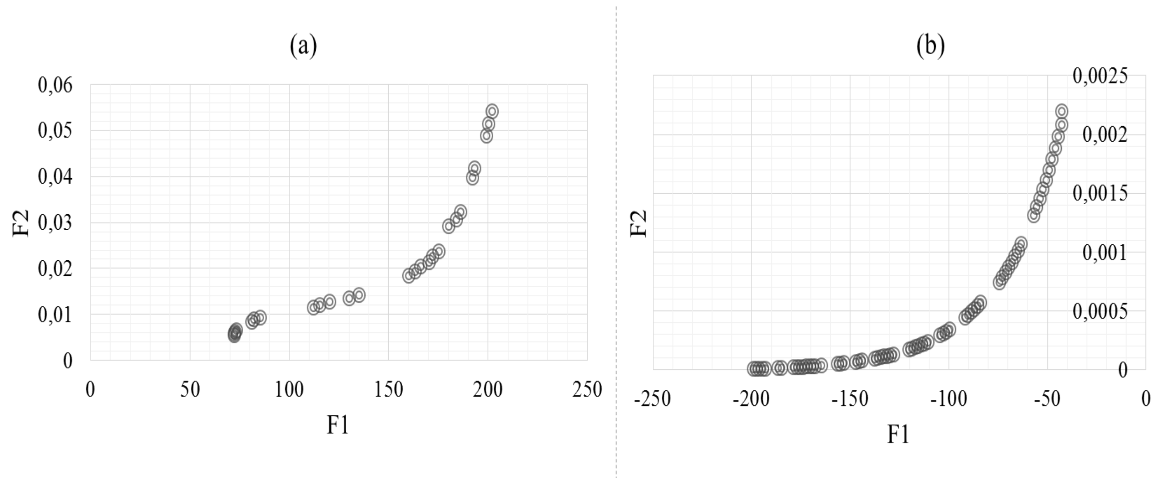


Figure 40 - Pareto front; (a) NSGA-II; (b) NSDE

The analysis of this behaviour of the algorithms in different instances of the problem led to the conclusion that, once solutions with positive values for the profit objective function were attained, NSDE then smoothly evolved to a packed and well-spread front. This goal was effortlessly accomplished by NSGA-II, which, in turn, computed improved solutions with better values for the objective functions, consequently expanding the front. These features led to the development of the hybrid approach. NSGA-II is used in a first phase to compute good extreme values and a few solutions spread along the Pareto front, which already present satisfactory values for both objective functions. After a few number of generations without improving both objective results (50 generations were considered in computational experiments), NSDE is used to further expand and fill up the front.

After the implementation of the hybrid EA, further tests have been done by varying the control parameters to analyze its performance according to different sets of parameters. The hypervolume indicator has been used throughout this algorithm refinement process to assess and compare the quality of the fronts obtained in the computational experiments.

Moreover, the behavior of the hybrid algorithm was evaluated with data subject to uncertainties. As mentioned previously, the load flexibility provided by each cluster for each time slot (LF_{ct}) is considered uncertain input data, to account for circumstances in which the end-user is not able to provide to the EBAg the load flexibility previously committed.

Three scenarios were created to evaluate the algorithm behavior in each of them: 1. Baseline Scenario - reliability equal to 100% is considered, that is, there is no uncertainty ($\theta_{ct} = 0$) in the load flexibility provided in each time slot by each cluster; 2. Daily Scenario - a range of reliability ($90\% \leq \theta_c \leq 100\%$) is considered in the load flexibility provided by each cluster and this value is the same in all time slots ($LF_{ct}{}' = LF_{ct} + LF_{ct}.\theta_c$); 3. *Real-time* Scenario - a range of reliability ($90\% \leq \theta_{ct} \leq 100\%$) is considered in the load flexibility provided by each cluster in each time slot, that is, the reliability in each time slot can be different ($LF_{ct}{}' = LF_{ct} + LF_{ct}.\theta_{ct}$).

After the execution of 100 tests for each scenario, it was possible to conclude that the algorithm had a good performance in all scenarios, with the Pareto optimal front presenting generally a good spread. Illustrative results (of an average run) can be seen in Figure 41 to Figure 42.

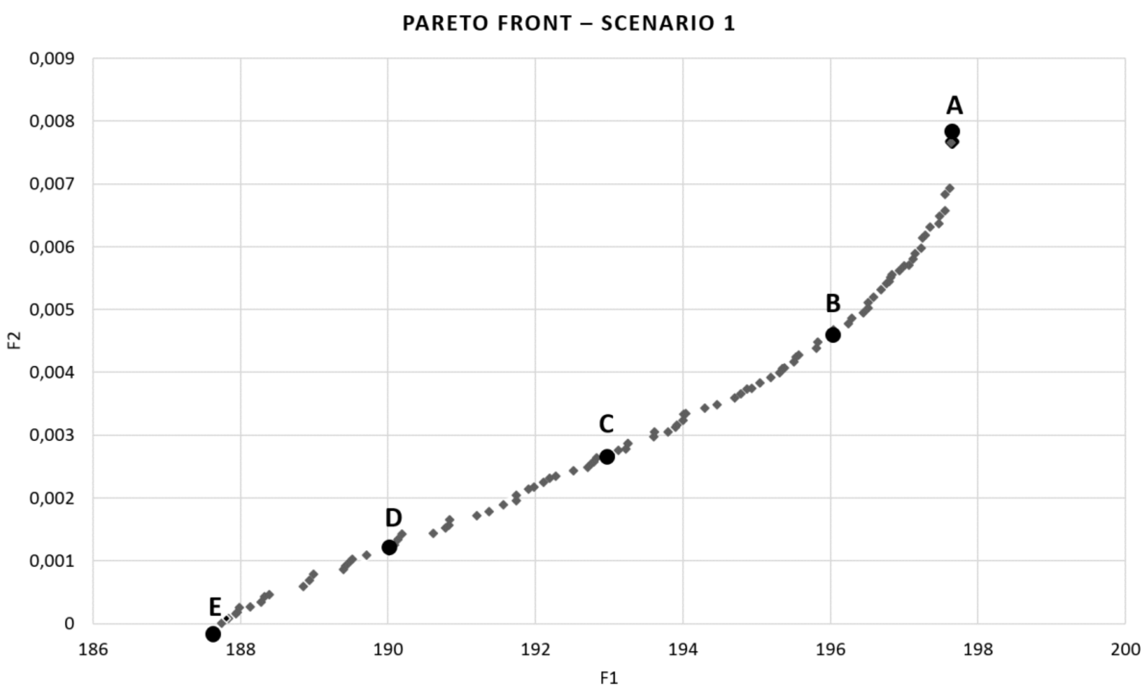


Figure 41 – Pareto Front in scenario 1

The hybrid algorithm presents a better performance in scenario 1, achieving the extreme solutions faster and with better objective function values in comparison to the other scenarios. Scenario 3 is the one in which the worst performance was verified, since it was difficult to achieve the extreme solutions and the results were more diverse, displaying a higher standard deviation. That is, the higher the uncertainty less good is the algorithm performance.

The maximum value obtained for F1 was 197.65€, while the average value of the solutions of F1 is 193.37€. 53.64% of the best solutions of each test present a value superior to the average, and 14.55% present a profit higher than 195€. The minimum value of profit achieved is 186€ and the corresponding standard deviation for all tests is 3.17€ (Figure 41).

In scenario 2 the maximum value obtained for F1 was 195.48€, while the average value of the solutions of F1 is 175.37€. 40.02% of the best solutions of each test present a value superior to the average and 11.16% present a profit higher than 180€. The minimum value of profit achieved is 151.59€ and the standard deviation for all tests is 11.9€ (Figure 42).

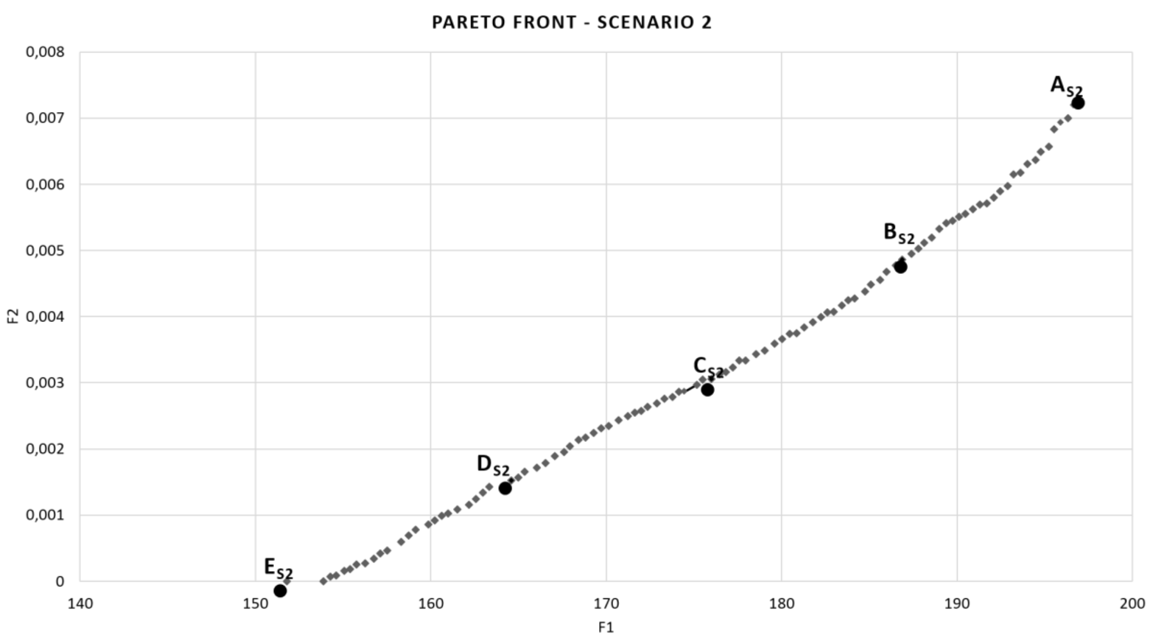


Figure 42 - Pareto Front in scenario 2

In scenario 3 the maximum value obtained for F1 was 193.93€, while the average value of the best solutions of F1 is 148.76 €. 36.26% of the best solutions of each test present a value superior to the average, and 6.62% present a profit bigger than 130€. The minimum value of profit achieved is 105.6€ and the medium standard deviation of all tests is 25.76€ (Figure 43).

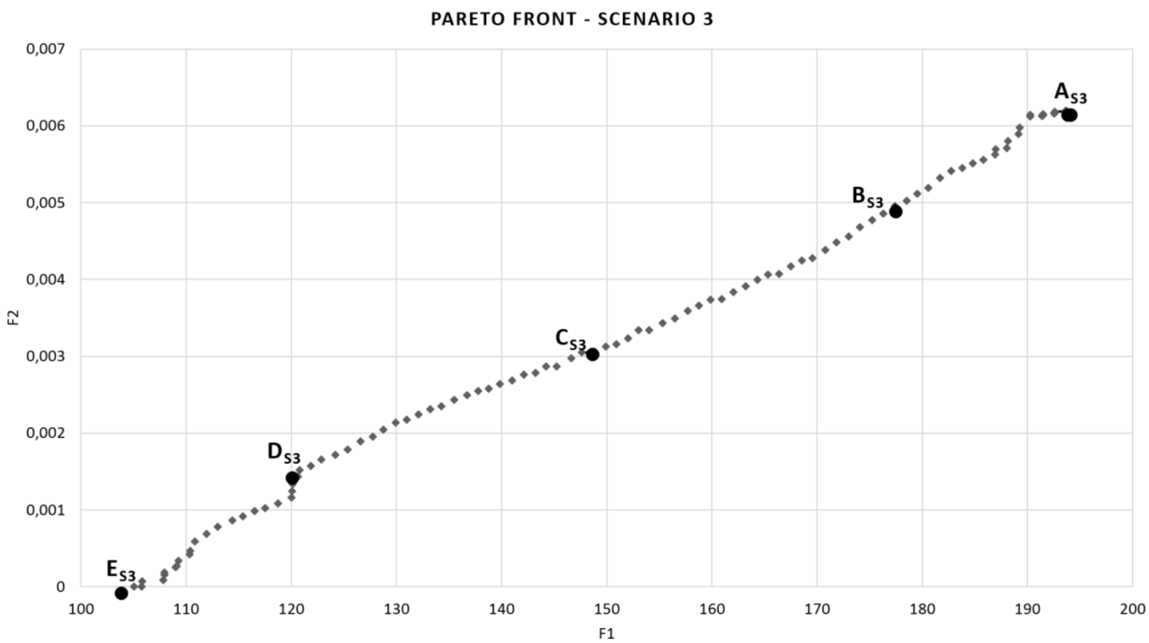


Figure 43 - Pareto Front in scenario 3

Figure 44 shows the hypervolume obtained in each iteration of the algorithm. After 500 iterations, it can be seen that the hypervolume gets stable, in some way enabling to conclude that the algorithm converged to the Pareto front.

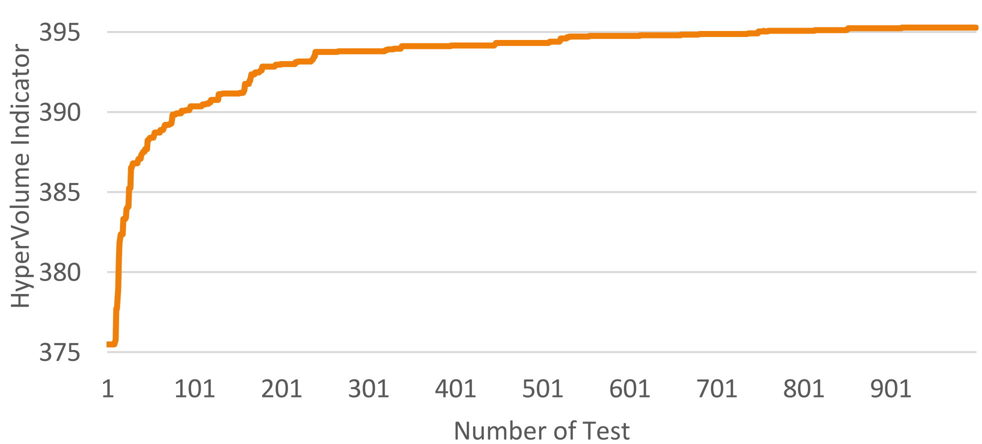


Figure 44 - Hypervolume for 1000 runs of the algorithm

5.2 Model Results and Discussion

This section presents some illustrative results of the optimization model created for an EBAg with multi-objective evaluation aspects (economic and fairness) of the merits of potential solutions. The hybrid approach based on an EA coupled with DE displayed an improved performance to obtain a well-spread and populated Pareto optimal front.

These results are illustrative of the extensive computational experiments carried out. More tests in real-world conditions should be performed to assess the true value of the EBAg concept. Also, the selection of a solution from the Pareto optimal front to be implemented is out of scope of the thesis. However, this is an important component that needs to be incorporated in future research.

The Pareto optimal front selected for the analysis is displayed in Figure 41. The individual optimal solutions (maximizing EBAg profits – F1 and minimizing inequity – F2) and three other solutions selected as good compromise solutions are displayed in black.

In solution **A**, the one that maximize the EBAg profits, the best value of F1 is obtained with 14 278 kWh of flexibility provided by load shedding with remnant of 16.53 kWh that could not be offered due to the cluster unavailability, leading to a profit of 197.6 € and 0.8% for the inequity indicator.

Solution **B** on the Pareto front could offer a flexibility of 14 222 kWh, with a remnant of 16.25 kWh not provided, achieving a profit of 196.78€ and 0.49% for the inequity indicator.

Solution **C** establishes a compromise between the objective functions offering a flexibility of 13 989 kWh, with a remnant of 16.17 kWh not provided, achieving a profit of 193.37€ and 0.32% for the inequity indicator.

Solution **D** on the Pareto optimal front could offer a flexibility of 13 735 kWh, with a remnant of 16.06 kWh not provided, achieving a profit of 190.29€ and 0.15% for the inequity indicator.

In solution **E**, the one that minimizes inequity among clusters, 13 736 kWh of flexibility were provided by load shedding in clusters with a remnant of 15.9 kWh not provided, leading to a profit of 186.03€ and 0% for the inequity objective function.

These results illustrate the conflicting nature of the objective functions maximizing the EBAg profit and minimizing the inequity among the end-user clusters in offering load flexibility. The higher the load flexibility provided by the end-users is, the higher the EBAg profit is.

Figure 45 displays the physical representation of solution C, i.e. the amount of power that the EBAg is capable to offer to the SO in each time slot (Pt), the amount of power that the EBAg effectively uses from all clusters in each time slot (Lct), and the remnant which consists in the power available from the end-user but not used by the EBAg to offer to the SO. To better understand the results and figures we remind that positive flexibility means that there exists flexibility to decrease consumption and negative flexibility means that there exists flexibility to increase consumption.

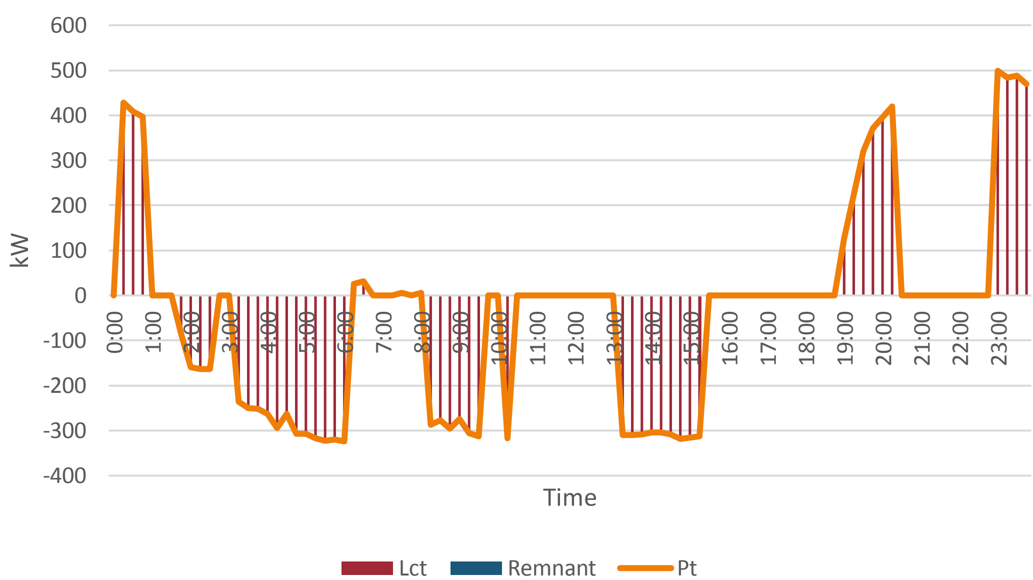


Figure 45 - Physical representation of solution C

In Figure 46 the positive flexibility of all clusters is presented, i.e., the amounts all clusters compromised to offer to the EBAg an energy **consumption of 1 416.89 kWh during one day with a maximum power of 498.78 kW. The aggregation of all clusters compromised** its offer in 98%, since the global flexibility provided to the EBAg was **1 388.89** kWh, with a remnant, that is, positive flexibility not used, of **27.99** kWh in one day.

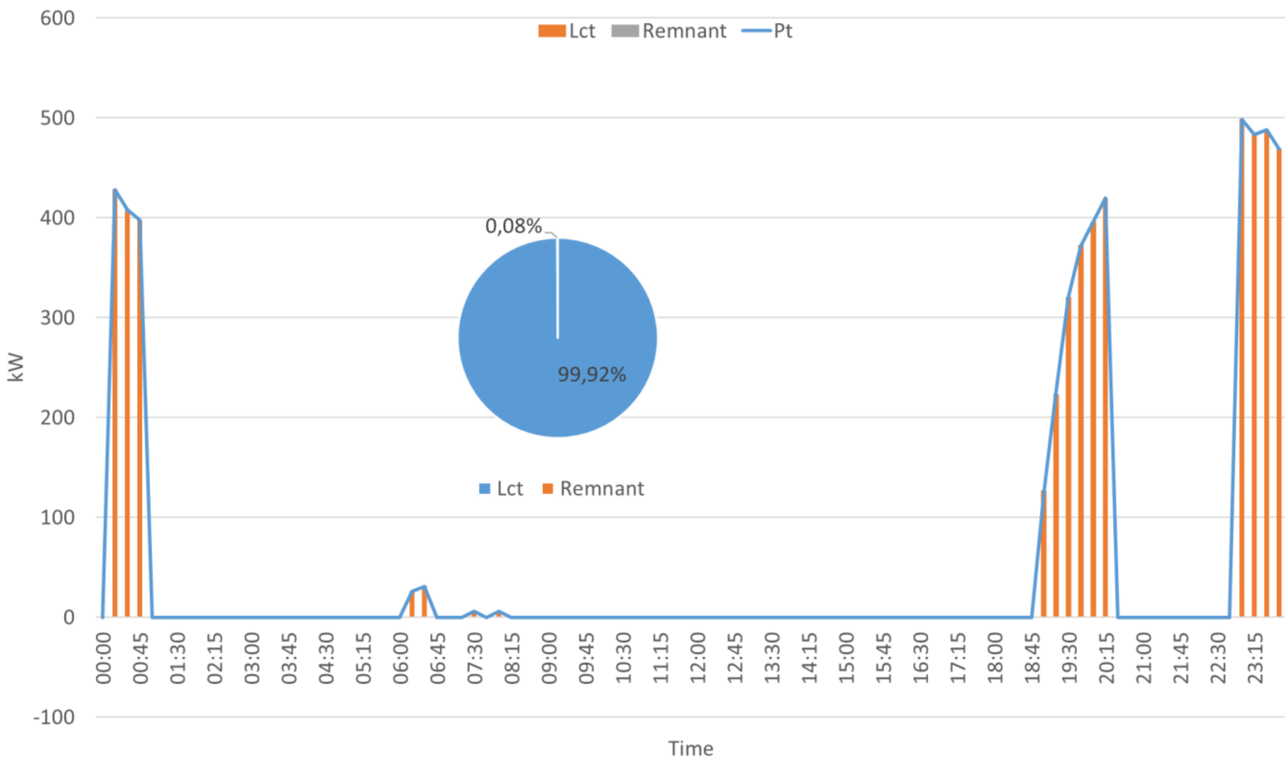


Figure 46 – Positive Flexibility of all clusters

In Figure 47 the negative flexibility of all clusters is presented, i.e. the amount all clusters compromised to offer to the EBAg an energy consumption of **2 468.83** kWh during one day with a maximum power of 323.9 kW. The aggregation of all clusters compromised its offer in 98.92%, since the global flexibility provided to the EBAg was **2 442.21** kWh, with a remnant, that is, positive flexibility not used of **26.63** kWh in one day.

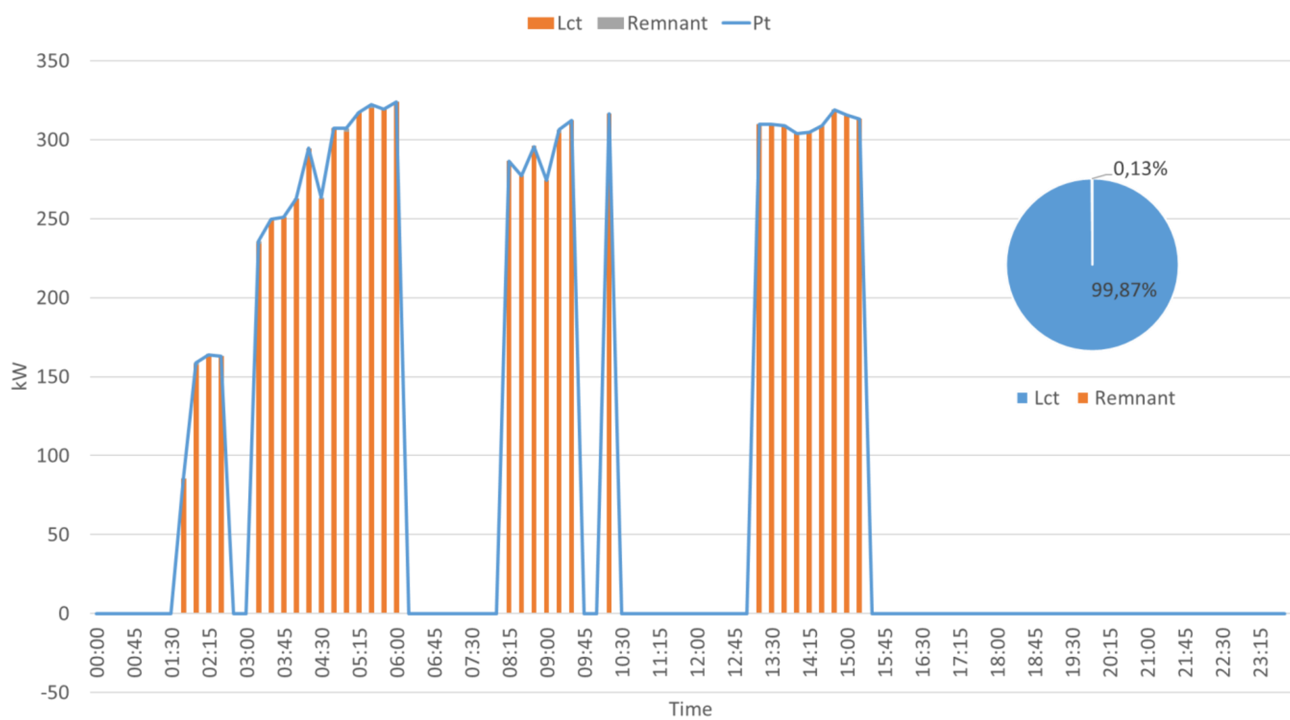


Figure 47 – Negative Flexibility of all clusters

In Figure 48 the load diagram before and after the algorithm execution is presented for cluster 1.

In the left-hand side, the positive flexibility of cluster 1 is presented, i.e. the amount cluster 1 compromised to offer to the EBAg an energy consumption of 108.48 kWh during one day, achieving a maximum power of 49.49 kW during that period. This cluster compromised its offer in 100%, since all the flexibility provided by cluster 1 was used by the EBAg to provide AS to the SO.

In the right-hand side the negative flexibility of cluster 1 is presented, i.e. the amount cluster 1 compromised to offer to the EBAg an energy consumption of 216.08 kWh one day, achieving a maximum power of 31.99 kW during that period. This cluster compromised its offer in 97.8%, since from the total flexibility provided by cluster 1 to the EBAg 211.28 kWh were used b, with a remnant not used of 4.79 kWh in one day.

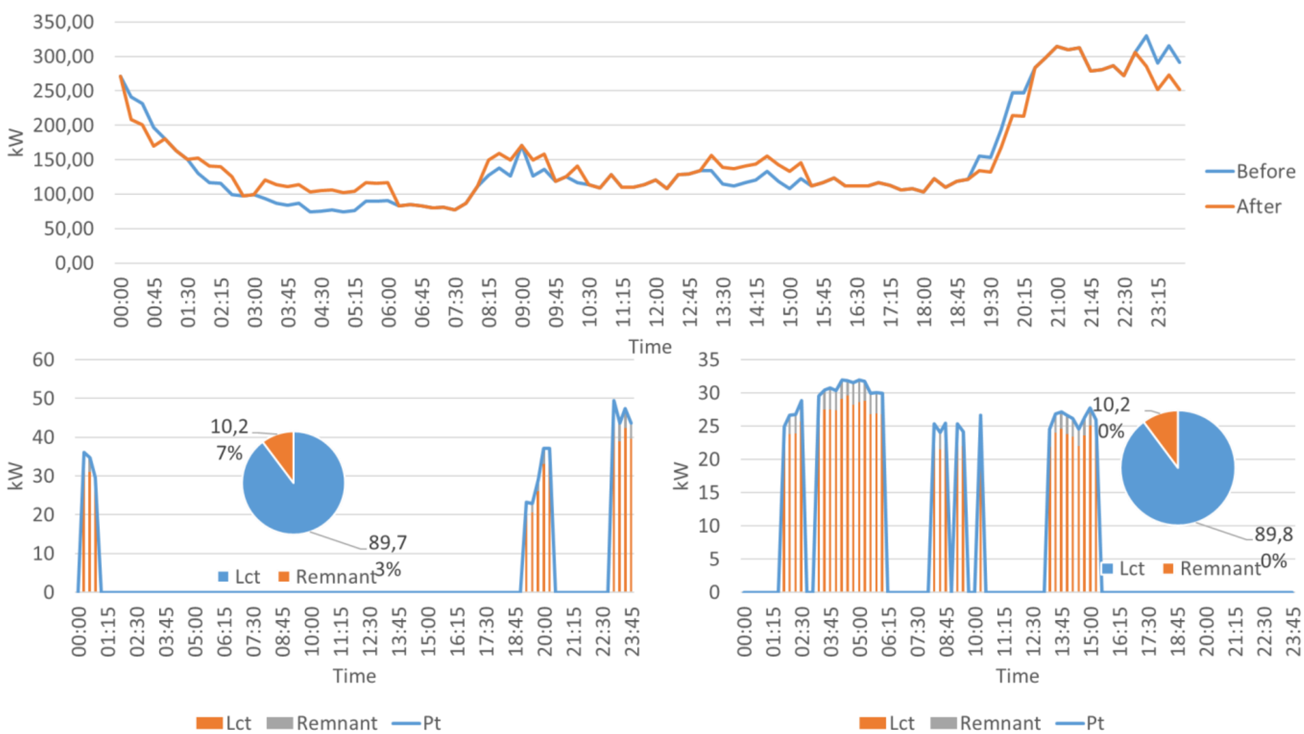


Figure 48 - Cluster 1 Results

In Figure 49 the load diagram before and after the algorithm execution is presented for cluster 2.

In the left-hand side the positive flexibility of cluster 2 is presented, i.e. the amount cluster 2 compromised to offer to the EBAg an energy consumption of 281.54 kWh during one day, achieving a maximum power of 110.84 kW during that period. This cluster compromised its offer in 99.4%, since from the total flexibility offered by cluster 2 279.95kWh were used by the EBAg, with a remnant not used of 1.59 kWh in one day.

In the right-hand side the negative flexibility of cluster 2 is presented, i.e. the amount cluster 2 compromised to offer to the EBAg an energy consumption of 646.79 kWh during one day, achieving a maximum power of 97.18 kw during that period. This cluster compromised its offer in 100%, since the total flexibility provided by cluster 2 was used by the EBAg.

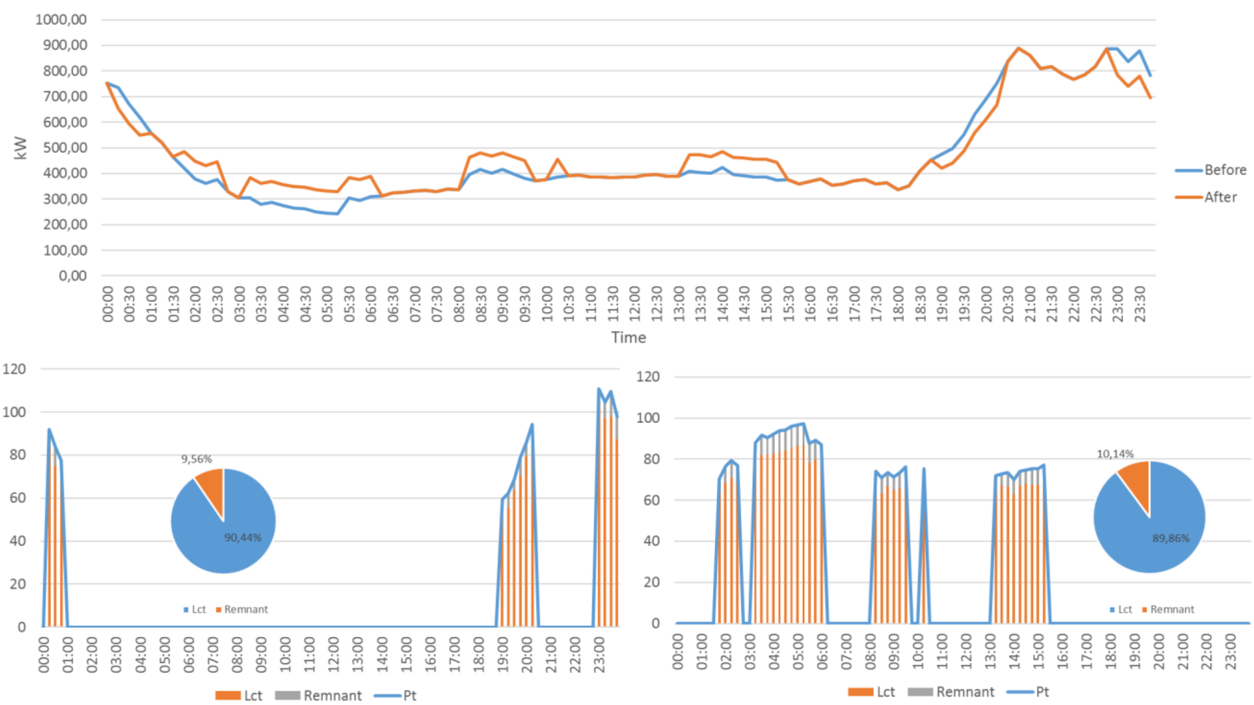


Figure 49 - Cluster 2 Results

In Figure 50 the load diagram before and after the algorithm execution is presented for cluster 3.

In the left-hand side the positive flexibility of cluster 3 is presented, i.e. the amount cluster 3 compromised to offer to the EBAg an energy consumption of 354.91 kWh during one day, achieving a maximum power of 133.61 kW during that period. This cluster compromised its offer in 100%, since the total flexibility provided by cluster 3 was used by the EBAg.

In the right-hand side the negative flexibility of cluster 3 is presented, i.e., the amount cluster 3 compromised to offer to the EBAg an energy consumption of 664.31 kWh during one day, achieving a maximum power of 101.89 kW during that period. This cluster compromised its flexibility offer in 99.14%, since 658.58 kWh were used by the EBAg, with a remnant not used of 5.73 kWh in one day.

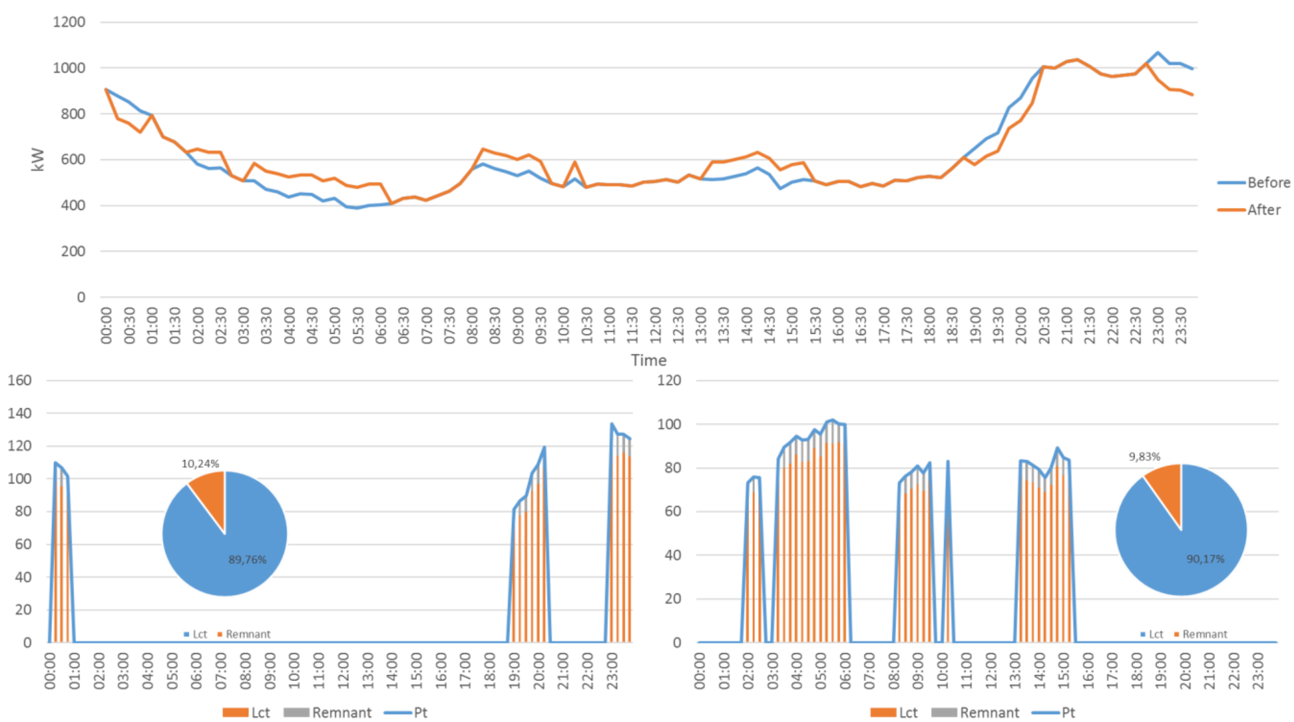


Figure 50 - Cluster 3 Results

In Figure 51 the load diagram before and after the algorithm execution is presented for cluster 4.

In the left-hand side the positive flexibility of cluster 4 is presented, i.e. the amount cluster 4 compromised to offer to the EBAg an energy consumption of 309.54 kWh during one day, achieving a maximum power of 122.55 kW during that period. This cluster compromised its flexibility offer in 99.5%, since 308.00 kWh were used by the EBAg, with a remnant not used of 1.54 kWh in one day.

In the right-hand side the negative flexibility of cluster 4 is presented, which the cluster 4 compromised to offer to the EBAg an energy consumption of 521.01 kWh during one day, achieving a maximum power of 87.02 kW during that period. This cluster compromised its offer in 100%, since the total flexibility provided was used by the EBAg.

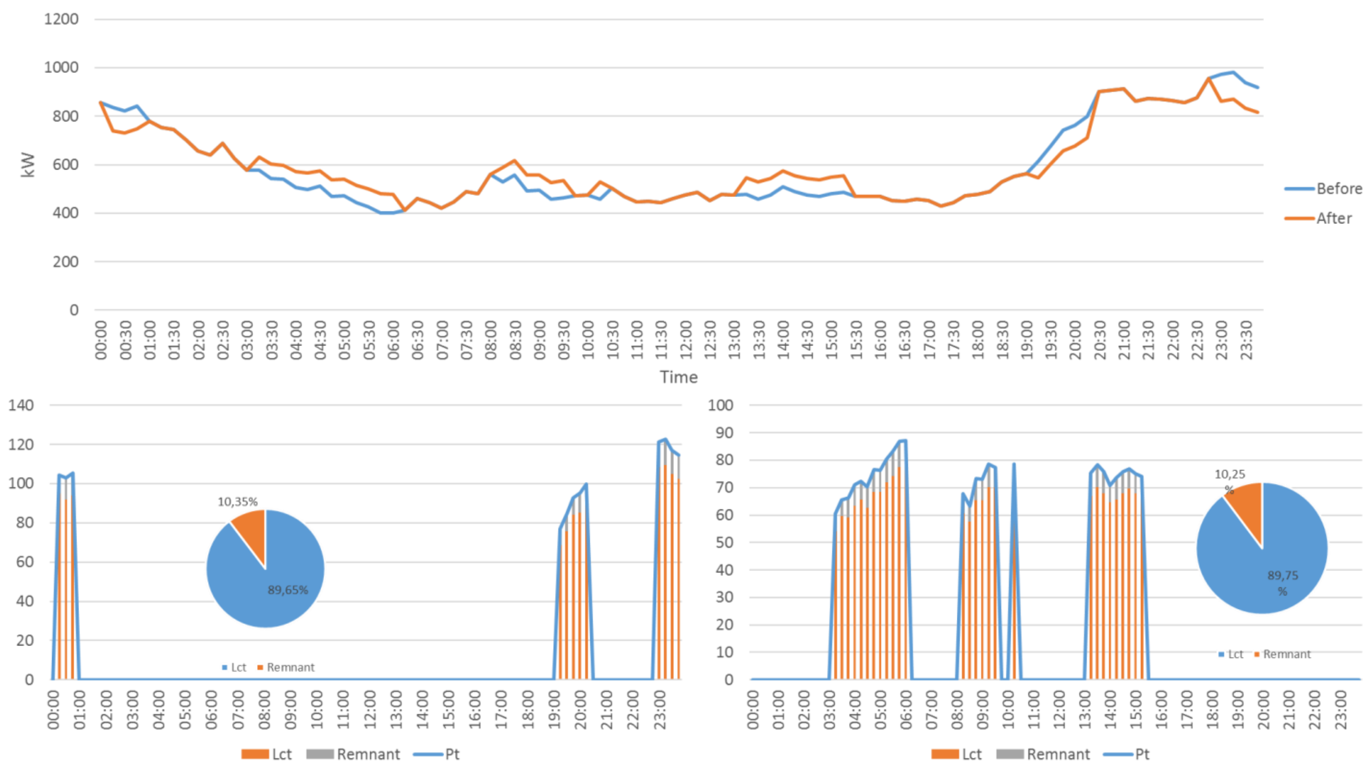


Figure 51 - Cluster 4 Results

In Figure 52 the load diagram before and after the algorithm execution is presented for cluster 5.

In left-hand side the positive flexibility of cluster 5 is presented, i.e. the amount cluster 5 compromised to offer to the EBAg an energy consumption of 182.28 kWh during one day, achieving a maximum power of 77.07 kw during that period. This cluster compromised its offer in 98.5%, since from the total flexibility provided 179.58 kWh were used by the EBAg, with a remnant not used of 2.70 kWh in one day.

In right-hand side the negative flexibility of cluster 5 is presented, i.e., the amount cluster 5 compromised to offer to the EBAg an energy consumption of **262.65** kWh during one day, achieving a maximum power of 50.38 kW during that period. This cluster compromised its offer in 100%, since the total flexibility provided was used by the EBAg.

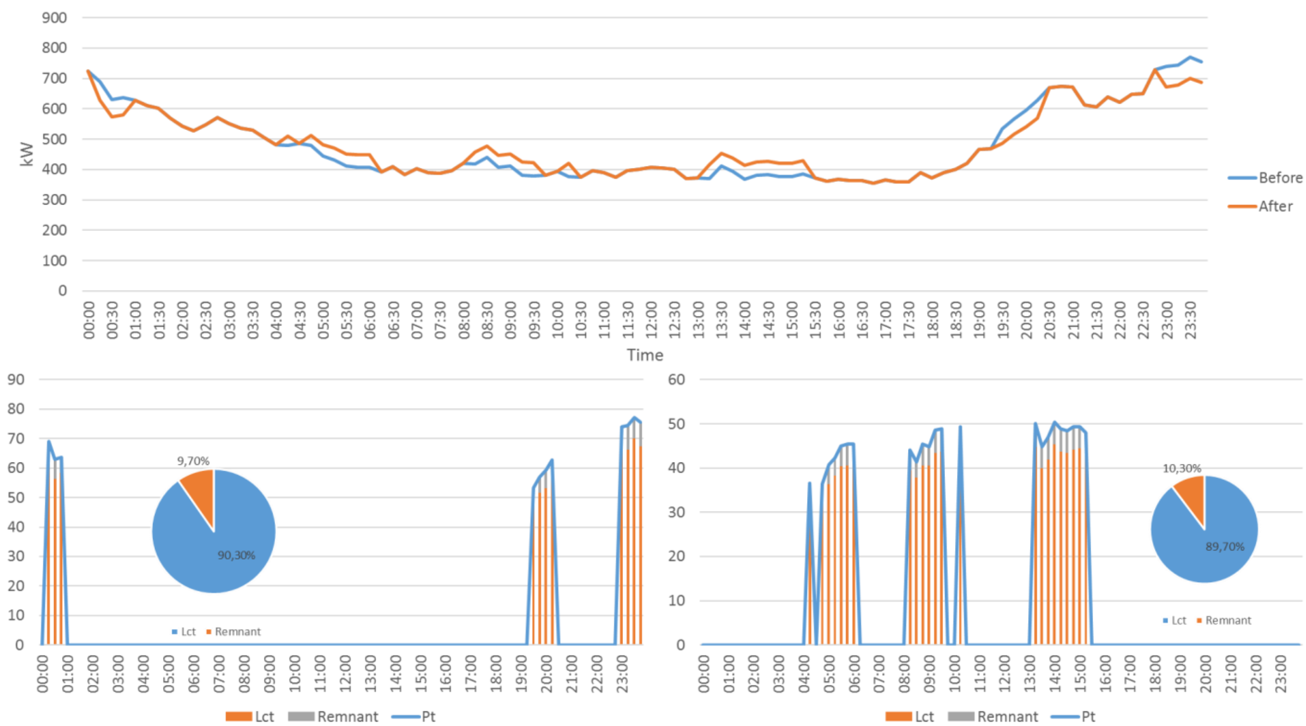


Figure 52 - Cluster 5 Results

In Figure 53 the load diagram before and after the algorithm execution is presented for cluster 6.

In the left-hand side the positive flexibility of cluster 6 is presented, i.e. the amount cluster 6 compromised to offer to the EBAg an energy consumption of 112.09 kWh during one day, achieving a maximum power of 39.80 kW during that period. This cluster compromised its offer in 93.4%, since 104.65 kWh of flexibility were used by the EBAg, with a remnant not used of 7.44 kWh in one day.

In the right-hand side the negative flexibility of cluster 6 is presented, i.e. the amount cluster 6 compromised to offer to the EBAg an energy consumption of 92.69 kWh during one day, achieving a maximum power of 25.96 kW during that period. This cluster compromised its offer in 96.5%, since from the total flexibility provided 89.43 kWh were used by the EBAg, with a remnant not used of 3.26 kWh in one day.

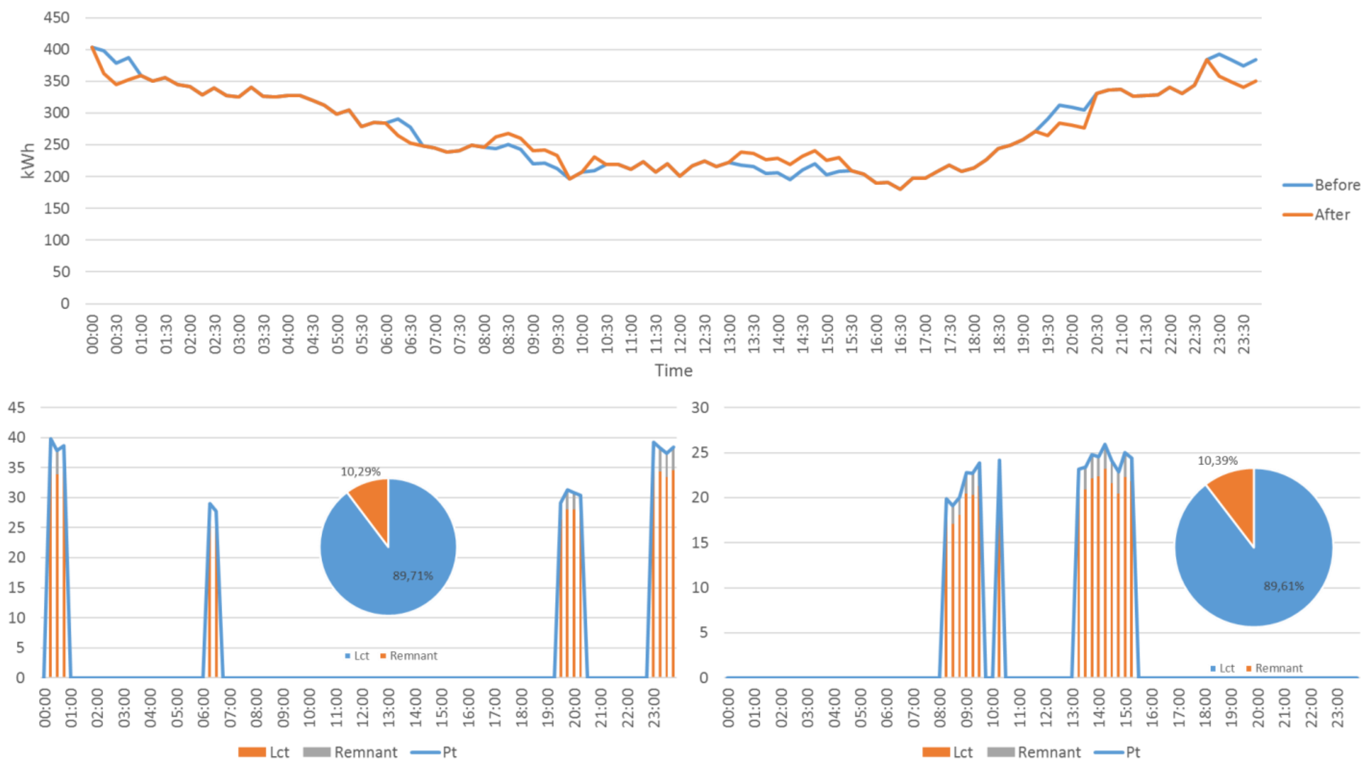


Figure 53 - Cluster 6 Results

In Figure 54 the load diagram before and after the algorithm execution is presented for cluster 7.

In the left-hand side the positive flexibility of cluster 7 is presented, i.e., the amount cluster 7 compromised to offer to the EBAg an energy consumption of 40.45 kWh during one day, achieving a maximum power of 17.61 kw during that period. This cluster compromised its offer in 63.6%, since from the total flexibility provided 25.73 kWh were used by the EBAg, with a remnant not used of 14.72 kWh in one day.

In the right-hand side the negative flexibility of cluster 7 is presented, i.e., the amount cluster 7 compromised to offer to the EBAg an energy consumption of 42.15 kWh during one day, achieving a maximum power of 11.33 kW during that period. This cluster compromised its offer in 69.53%, since 29.31 kWh of flexibility were used by the EBAg, with a remnant not used of 12.84 kWh in one day.

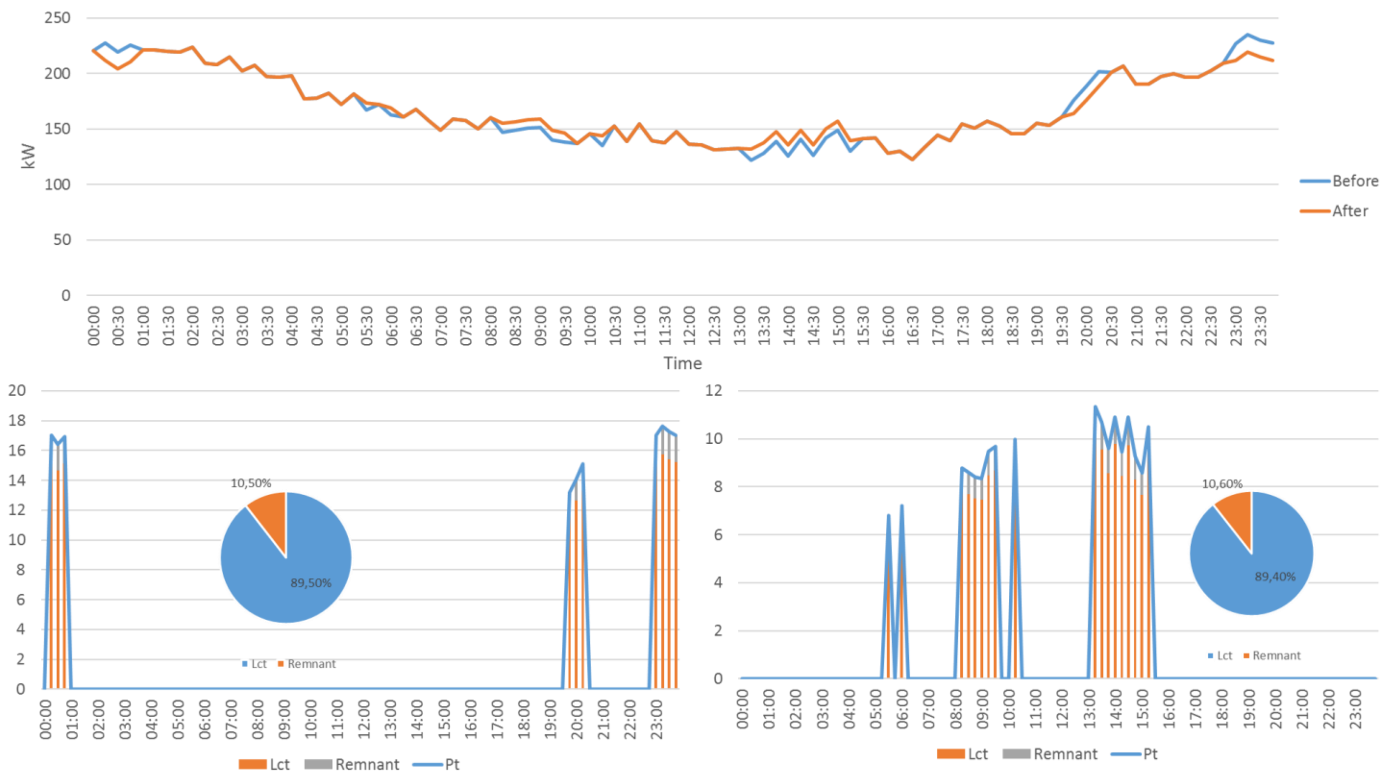


Figure 54 - Cluster 7 Results

In Figure 55 the load diagram before and after the algorithm execution is presented for cluster 8.

In the left-hand side the positive flexibility of cluster 8 is presented, i.e., the amount cluster 8 compromised to offer to the EBAg an energy consumption of **27.60** kWh during one day, achieving a maximum power of 9.06 kW during that period. This cluster compromised its offer in 100%, since the total flexibility provided by cluster 8 was used by the EBAg.

In the right-hand side the negative flexibility of cluster 8 is presented, i.e., the amount cluster 8 compromised to offer to the EBAg an energy consumption of **23.16**kWh during one day, achieving a maximum power of 5.13 kW during that period. This cluster compromised its offer in 100%, since all the flexibility provided was used by the EBAg.

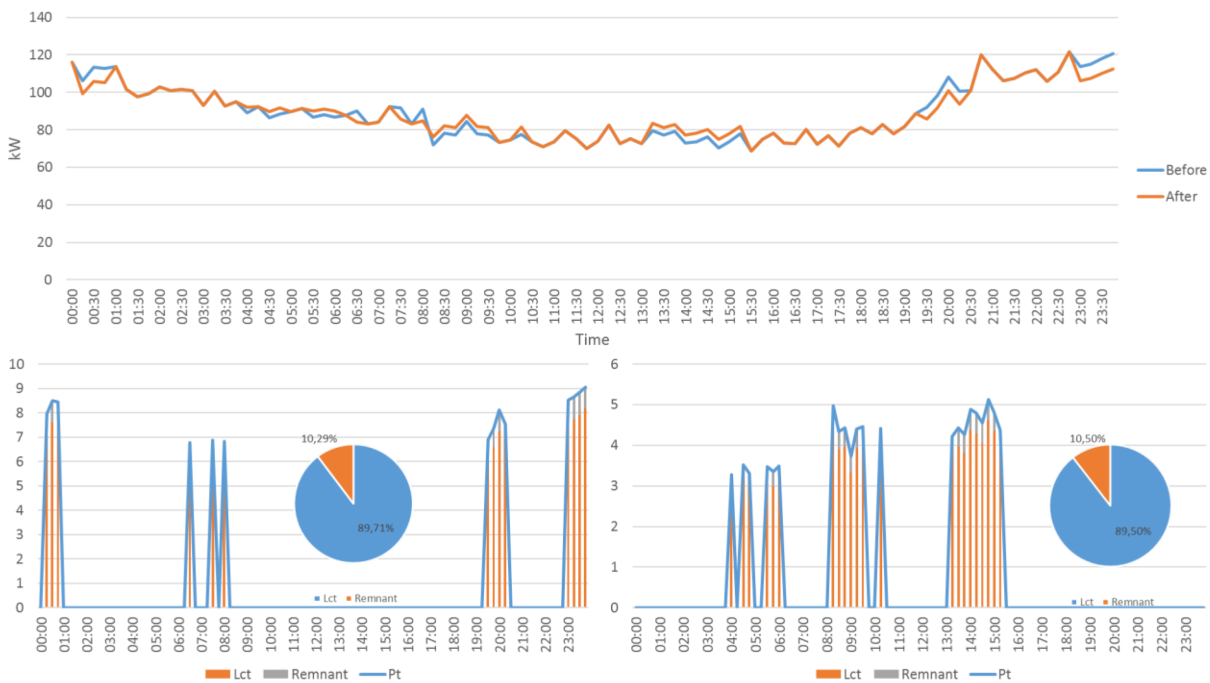


Figure 55 - Cluster 8 Results

5.3 Concluding Remarks

This section presented the analysis of results of the hybrid approach based on an evolutionary algorithm coupled with a differential evolution algorithm, which displayed an improved performance to obtain a well-spread and populated Pareto front, to deal with the main characteristic of the EBAg model.

Extensive computational experiments have been carried out, which contributed to tune the main technical parameters of the algorithms, such as crossover and mutation probabilities, uncertainty scenarios, etc. The combination of NSGA-II and NSDE proved to be the best approach after numerous attempts to increase the performance of each algorithm individually. NSGA-II quicky finds good extreme solutions and NSDE provides a well-spread and populated front.

It is possible to conclude that the hybrid algorithm also presents a good performance even when subject to uncertainties, i.e., the load flexibility provided by the end-user (thus accounting for human factors).

Real data information gathered during one year from households to obtain the load diagrams was used to supply some coefficients of the model in the case study herein presented.

The illustrative results were presented to demonstrate the viability of the of the EBAg concept, from the points of view of responding to grid requests and using end-user's flexibility provided.

Part III

Energy Management Systems Aggregator: Uncertainty and Robustness

6. Chapter 6 - Uncertainty and robustness in optimization [7]

6.1 Introduction

This chapter presents background information and concepts regarding uncertainty and robustness analysis. A brief literature review is presented regarding approaches to robustness analysis in MOO models.

Most real-world optimization problems are characterized by various forms of uncertainty stemming from factors such as data variable in time, incomplete data, data that is contradictory between diverse sources or controversy for different players of the process, solutions that cannot be implemented exactly, etc. [284–286]. The concept of degree of robustness proposed in [287,288,288–292], which is based on the behavior of a solution in its neighborhood, is presented as the basis of our methodological approach to robustness analysis. The degree of robustness is normally incorporated into EAs, being operationalized in the computation of the fitness value assigned to solutions. Non-dominated solutions are classified according to their degree of robustness. The information on the degree of robustness of solutions is provided to support the selection of a robust compromise solution. This concept of degree of robustness allows to exert a control on the desired level of robustness of the solution obtained.

6.1.1 Characterization of Uncertainty

Decision making in a context of uncertainty is a frequent situation in real problems, namely in what respects activity planning in several fields. The modeling of uncertain data in mathematical models through probability distributions has been the main approach to incorporate in an explicit way information that is not completely known in the model construction phase. However, uncertainty can stem from different sources or be classified in different types, not being adequate, in general, to represent probabilistically all the uncertain information associated with mathematical models, especially

[7] This chapter is partially based on Carreiro, A., Jorge, H., Antunes, CH., 2016. Assessing the robustness of solution to multi-objective model for an energy management system aggregator. 2016 IEEE Symposium Series on Computational Intelligence (IEEE SSCI 2016), https://doi.org/10.1109/SSCI.2016.7849845

if the available information is insufficient for that purpose [293]. Therefore, models should cope with distinct forms to capture uncertainty in order to offer robust solutions, i.e. solutions that present a good performance for a plausible range of variation of uncertain information.

6.1.1.1 Models that incorporate uncertainty

Dealing with uncertainty includes building models that incorporate uncertain data and subsequently using approaches to determine solutions to these models that exhibit a certain degree of performance for a range of variation of those data. Although there is no single model that can incorporate any type of uncertainty, the model developed should be appropriate to the types of uncertainty at stake and/or the quantity and quality of information available. The most common approaches to deal uncertainty in (single and multiple objective) optimization models are: fuzzy programming [294], interval programming [295,296], based on scenarios [284,293,297], stochastic programming [298] and robust programming [299].

In fuzzy programming, the uncertainty is captured through fuzzy sets, which are generally used when there is no statistical information available or when it is necessary to deal with qualitative descriptions corresponding to expert's statements about the data or the impact of alternatives. While in the classical model of sets the relationship between an object and a set is of belonging or not belonging, in a fuzzy model an object can also belong partially to a set, a degree of belonging existing in this relationship. The theory of fuzzy sets developed by Zadeh [300] is an extension of classical set theory, in which the degree of belonging of an element to a set takes a value in the range [0, 1] instead of just 0 or 1. A fuzzy set is a class of objects where there is not a well-defined border between the objects belonging to the class and the ones outside the class. This theory was developed to deal with the underlying complexity descriptions of subjective processes or misunderstandings.

Interval programming considers that some or all the uncertain data of the problem are described through intervals rather than a single value. In its basic formulation, intervals are more similar to scenarios, attempting to capture every possible future value of the relevant data (i.e., uncertain but bounded). Intervals can be considered as a special case of fuzzy values or uniform distribution corresponding to no additional information beyond the range of possible values.

In scenario-based models the uncertain data is estimated globally to consider their correlations and build different structured futures. Although this approach does not require a probability distribution, the concept of "most likely scenario" is often invoked in a qualitative sense, which sometimes means that all other settings will be ignored. The scenarios are possible (future) sets of data instances, always requiring a model that provides the means to evaluate the consequences of a decision in every possible scenario. Assigning probabilities to scenarios is a common practice, usually through a set of values estimated by an expert.

Stochastic programming requires the existence of sufficient statistical data for developing the probability distribution functions of uncertain data or using subjective probabilities. Stochastic programming can be seen as an approach to model uncertainty considering scenarios that occur with different probabilities to describe the problem data [298]. The two major difficulties with this kind of approach are that it is not easy to obtain in practice the exact distribution for the data and so enumerate the scenarios that collect this distribution, as well as the size of the resulting optimization model drastically increases according to the number of scenarios, which entails major challenges in terms of computational effort. A technique commonly used to tackle this kind of uncertainty is to transform the non-deterministic problem into a deterministic one, by substituting all the parameters of the stochastic model for their expected values. Thus, the optimal solution is the one with the best expected value.

Kouvelis and Yu [299] introduced robust programming based on the concept of robustness in the sense of min-max solutions, i.e. determining the solution that, in the worst case, has the best value of the attribute under evaluation. The basic robustness formulation ignores any additional information, such as possible probability distributions. The purpose is to determine robust solutions that are somehow immune to disturbances in the values of model data.

6.1.2 Concepts of Robustness

The notion of robustness is not used uniformly in the literature, probably due to the diversity of situations of the real-world problems, in which uncertainty is an inherent feature. One of the first concepts of robustness in optimization problems was presented by Gupta and Rosenhead [301] and several meanings of robustness and ways to deal with uncertainty to derive robust solutions have been introduced by different authors with several robustness interpretations [302,303], Vincke [304] distinguishes four different concepts of robustness, the starting point for future developments: robust decision [301,305], robust solution [299,306,307], robust conclusion and robust method [252,308–310].

Robust decision: The notion of robustness applied to decision problems was first introduced by Gupta and Rosenhead [301] in the context of sequential planning problems. In this type of problems, decisions are built over time in face of different sources of uncertainty. In this way, all decisions will affect future plans, limiting the number of good plans that can be achieved in the future. The robustness of a given decision is therefore based on maintaining flexibility. A decision is considered as more flexible as least it limits the number of good plans in the future. The ideal situation would be to be able to make decisions at a given time without limiting the different possible future decisions [305].

Robust solution: Mulvey [307] presented a general formulation for a model of single-objective robust optimization based on scenarios. In this formulation, a solution of an optimization model is defined as a robust solution if it remains close to the optimal solution in all scenarios. A model is classified as a robust model if it remains feasible in all scenarios. Kouvelis and Yu [299] use robustness in a more conservative sense, that is, the DM is at minimum risk (in the setting of discrete optimization problems using scenarios). For these authors, robust solutions are those whose values are the best in the worst scenario (which can be defined in various ways).

Robust conclusion: Roy [303] proposed the concept of strength, not only to solutions but, more generally, to conclusions (statements, recommendations). One conclusion is information inferred from the model and given to the DM during the decision process. This can be a proposition for a solution to the problem, but can also be a property or fact that may be useful to the DM. One conclusion is said robust if it is valid in all or almost all scenarios, a scenario being a set of possible values for the model data used to solve the problem.

Robust method: Vincke [252] proposed a formal definition of robustness also related to procedures and method. A procedure is an application that associates a solution to every instance of a problem. A method is a sequence of procedures, which allows obtaining different solutions for different implementations, for example, with different expressions of preferences. A method is robust if it provides valid results in all or most scenarios and where a scenario is a set of possible values for the model data and the method parameters [252,308,309].

In [299] robustness signifies that the solution is good in all or most scenarios, where a scenario is a group of possible values for the data model, and not bad in none.

As a conclusion, a common interpretation of robustness can be found in the literature: a solution is robust when it is immune to small perturbations, this is, when exposed to different conditions comparatively to a nominal one due to the uncertainty of some parameters (input data, decision variable values, etc.) the solution still performs well enough in terms of the objective function values.

6.1.3 Robustness in Multi-objective Optimization

The importance of robust optimization in the framework of meta-heuristics is recognized by Kouvelis and Yu who state that a considerable effort should be placed on the development of schemes to be applied to a large class of optimization problems [299].

MOO in face of uncertainties is very relevant for the exploitation of the results in practice, since slight difference in environmental conditions or variations in the solution structure after implementation can be crucial to overall operational success or failure. The thorough characterization of the whole set of non-dominated solutions is important to offer a global overview of the tradeoffs between the multiple objective functions for solutions located in different regions of the search space. However, some of these solutions, which could be of interest for the DM as adequate compromise solutions, in the sense they present a satisfactory balance between the multiple, conflicting and incommensurate objective functions, may be very susceptible to perturbations. Since the data to be supplied to the model is subject to several sources of uncertainty, solutions should be assessed for robustness, i.e., their performance in the multiple objective functions in face of data perturbations should be analyzed. In fact, data supplied to mathematical models often suffers from distinct sources of uncertainty due to difficulties associated with data estimation and collection, and even the dynamic and variable nature of some data, thus influencing the coefficients of objective functions, coefficients of constraints, and bounds of decision variables. Therefore, it is necessary to identify non-dominated solutions displaying not just satisfactory values for the conflicting objective functions but also being somehow insensitive to slight variations in the model data. That is, the algorithm to solve the MOO model should strive for robust solutions [292].

Some studies focused on robustness in MOO models and a comprehensive view of evolutionary MOO in uncertain environments is provided in [259,289,290,292,311–314]. Results regarding the design and applications of EA for MOO in the presence of uncertainty are presented in [315] and a survey of optimization in uncertain environments is presented in [316]. The need to generate robust solutions from EA is discussed in [317], proposing changes to standard EA to produce robust solutions. In [312] a reformulation of the ranking process associated with the selection operator is developed taking into account uncertainties in data and noise in the objective functions. An extension to Pareto dominance considering the uncertainty of the multi-objective functions within intervals is presented in [313], deriving a theory of "probabilistic dominance" able to orient the selection operators to obtain the Pareto set. The Robust Multi-Objective Genetic Algorithmic (RMOGA) is proposed in [314] to optimize two objectives: a fitness value and a robustness index enabling to analyze the tradeoffs among performance and robustness of solutions using distance metrics. Two robust MOO procedures are presented in [311,318] with the aim of finding a robust frontier composed by robust solutions instead of the global Pareto optimal front, by extending the techniques used in single objective robust optimization, assuming that the DM is not interested in finding global best solutions which may be too sensitive to small environmental changes. The concept of degree of robustness of non-dominated solutions is incorporated into an EA in [287,292], which is based on the behavior of the solution in its neighborhood when subject to perturbations in the decision variable space and the objective function coefficients. Two EA approaches to robustness analysis in MOO involving the degree of robustness concept imbedded in the fitness assessment of solutions are used in [290] and experiments were carried out in the problem of locating and sizing capacitors for reactive power compensation in electric radial distribution networks. An approach based on the classification of robustness regions of the Pareto optimal front is proposed in [319], distributing the solutions along the most robust regions according to parameter values and degree of robustness with the aim of finding the most robust Pareto front.

The next section briefly reviews an approach to evaluate non-dominated solutions based on the degree of robustness proposed in [287,290,292].

6.1.4 Degree of Robustness

In this section the approach using the degree of robustness associated with solutions developed in [287,288,288–291] is reviewed, which is the basis of our analysis. According to [287,288,288–291], a robust solution shall "behave well" in (slightly) different conditions, meaning that it is immune to small changes in the conditions it was designed for [292]. A robust solution must guarantee a good performance (regarding both feasibility and objective function values) even if (a slightly) different model coefficient is applied, vis-à-vis a nominal situation, due to the uncertainty associated with data gathering, estimates, etc. [288,290,292].

The degree of robustness of solution ***x*** is a value ***k***, such that (see Figure 56):

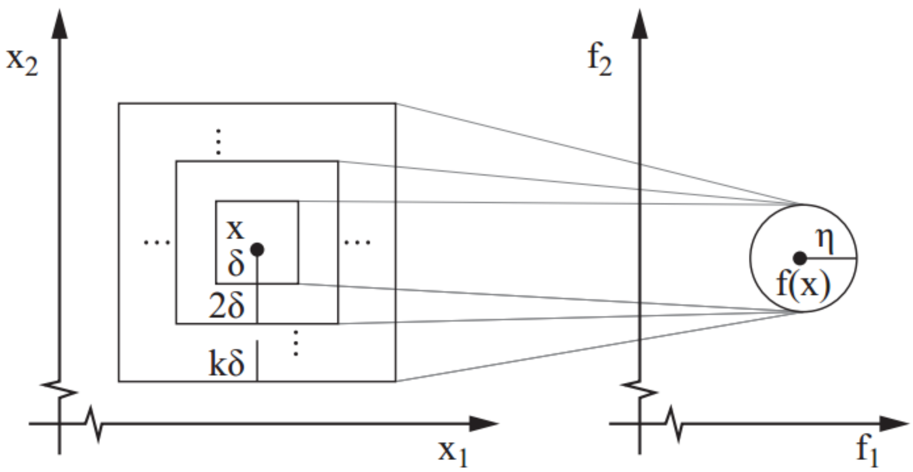


Figure 56 - Definition of neighborhoods in the decision variable space and objective function space [289]

(a) the percentage of solutions in the ***kδ***-neighborhood of ***x***, whose objective function values belong to the ***η*** neighborhood of ***f(x)***, is greater than or equal to a pre-specified threshold ***p***;

(b) the percentage of solutions in the ***(k+1)δ*** neighborhood of ***x***, whose objective function values belong to the ***η***-neighborhood of ***f(x)***, is lower than ***p***. The threshold ***p*** may be understood as a measure of exigency of the concept of degree of robustness. The degree of robustness *k* of a solution ***x*** is gradually computed as ***k*** increases (neighborhoods ***δ***, ***2δ***, …, ***kδ***), as well as the number of neighboring points of ***x*** (***h***, ***h+qh***, …, ***h+(k-1)qh***), such that ***h+(t-1)qh*** neighboring points (***t ∈ {1, …, k}***) are analyzed in the ***tδ***-neighborhood of ***x***. The ***p***, ***η*** and ***q*** parameter values can be different depending on the solution type (if solutions are non-dominated , or solutions are dominated or non-feasible).

6.1.4.1 Perturbation of the Objective Function Coefficients

It is assumed that perturbations may occur in any coefficient of objective function ***fr*** ($c_{r1}, c_{r2},\ldots, c_{rm}$), for $r = 1, \ldots, M$. The assessment of the degree of robustness of a solution ***x*** entails analyzing the neighborhood of the reference scenario ***s***, where ***x*** is a solution to the problem and $f^s(x)$ is the point in the objective space for the reference scenario ***s***. The underlying idea is to determine a set of neighborhoods $k\delta$ around the reference scenario ***s***, such that the images of ***x*** for these neighborhood scenarios are better than $f^s(x)$, for all objective functions, or still belong to a pre-specified neighborhood η around $f^s(x)$ in the objective space. The process begins by analyzing scenarios (coefficient instantiations) randomly generated inside a hyperbox of radius δ around ***s***. This neighborhood (hyperbox) is then progressively enlarged, in multiples of δ (δ, 2δ ,…), until the percentage of scenarios for which the images of ***x*** in the objective space that are better than $f^s(x)$ or belong to the neighborhood of $f^s(x)$ is not greater than a pre-defined threshold. This enables to assign a degree of robustness to solutions according to the number of hyperbox enlargements for which that condition is fulfilled (Figure 57).

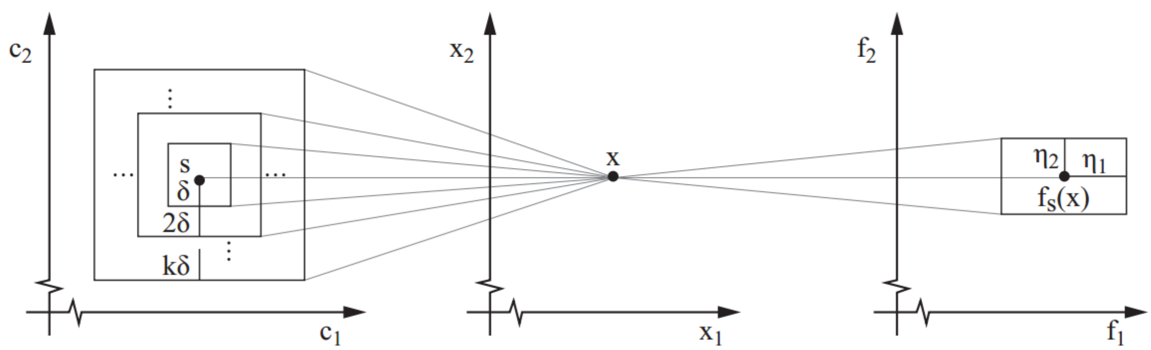


Figure 57 - Definition of neighborhoods in the scenario space and objective function space associated with a solution x (for 2-dimension spaces) [289]

The degree of robustness depends on the size of a δ-neighborhood of scenario ***s*** and the percentage of the ***h*** neighboring points whose objective function values for ***x*** are better than $f^s(x)$ or belong to the η-neighborhood of $f^s(x)$. Those ***h*** neighboring points are randomly generated around scenario ***s*** (see also [288,290,311]). The degree of robustness of solution x is a value k, such that (see Figure 57):

a) the percentage of scenarios s' in the $k\delta$-neighborhood of s, for which the objective function values $f^{s'}(x)$ that are better than $f^{s}(x)$ or that belong to the η-neighborhood of $f^{s}(x)$, is greater than or equal to a pre-specified threshold $p1$;

b) the percentage of scenarios s' in the $(k+1)\delta$-neighborhood of s, for which the objective function values $f^{s'}(x)$ that are better than $f^{s}(x)$ or that belong to the η-neighborhood of $f^{s}(x)$, is lower than $p1$. The degree of robustness k of a solution x determined in the reference scenario s is gradually computed as k increases (neighborhoods $\delta, 2\delta, \ldots, k\delta$), as well as the number of neighboring points of s ($h, h+qh, \ldots, h+(k-1)qh$), such that $h+(t-1)qh$ neighboring points ($t \in \{1, \ldots, k\}$) are analyzed in the $t\delta$ -neighborhood of s.

6.1.4.2 Perturbations of the Constraint Coefficients

For this case, a scenario is a set of possible values for the constraint coefficients (it can include the decision variable bounds) subject to perturbations. The computation of the degree of robustness of a solution x involves the analysis of the feasibility of x for the neighborhood of the reference scenario s. $f(x)$ is the point in the objective space for the reference scenario s, as well as for all possible scenarios. The feasibility of x varies for distinct scenarios, since each scenario (constraint coefficient instantiation) may correspond to distinct feasible regions. The aim is to compute a set of k neighborhoods around the reference scenario s, the radius of which is a multiple of a value ($k\delta$), such that x still is a feasible solution for those coefficient instantiations around the nominal (reference scenario).

Randomly generated scenarios inside a hyperbox of radius δ around reference scenario s are analyzed. This neighborhood is then progressively enlarged ($\delta, 2\delta, \ldots$) until the percentage of scenarios for which the solution x is a feasible solution is not greater than a pre-defined threshold. Again, this enables to assign a degree of robustness to solutions according to the number of hyperbox enlargements for which that condition is satisfied, which depends on the size of a δ-neighborhood of reference scenario s and the percentage of the h neighboring points for which the solution x is a feasible solution. The degree of robustness of solution x is a value k, such that:

a) The percentage of scenarios s' in the $k\delta$-neighborhood of s, for which the solution x is a feasible solution, is greater than or equal to a pre-specified threshold $p2$;

b) The percentage of scenarios s' in the $(k+1)\delta$-neighborhood of s, for which the solution x is a feasible solution, is lower than $p2$.

The degree of robustness ***k*** of a solution ***x*** is determined in the same way as explained above for the case of perturbations of the objective function coefficients.

6.1.4.3 Robustness Parameters

The radius of each neighborhood (around a solution or the reference scenario) is a multiple of the parameter **δ (δ ,2δ , ...).** This parameter reflects the DM's preferences about the base dimension of the neighboring solutions in the solutions space or the neighboring scenarios in the scenario space, such that the DM is indifferent for solutions or scenarios located therein. The parameter ***h*** sets the number of neighboring points of a solution or the reference scenario that are generated and analyzed. The higher the value of ***h***, more extensive the analysis is (however, the execution time of the algorithm will be higher). The vector parameter ***η*** reflects the threshold of indifference for each objective function. This parameter is used as the upper bound for the distance between the images of a solution ***x*** in a given scenario and in the reference scenario. Increasing the values of ***η*** (meaning that the DM is more tolerant to the differences in the objective function values) tends to increase the number of solutions with a higher degree of robustness. The thresholds ***p1*** and ***p2*** control the exigency of the degree of robustness. The parameter ***q*** is a value between 0 and 1, which is associated with the increase of the number of neighboring points that are analyzed in successive enlargements of the neighborhood of a solution or the reference scenario.

The values of the parameters ***p1***, ***p2***, ***η*** and ***q*** may be different depending on the solution type, that is, whether solutions are non-dominated or they are dominated or non-feasible. Due to the significant run time of this approach, it is advisable that the value of ***p1*** and ***p2*** should be higher for dominated and infeasible solutions, and the values of ***η*** and ***q*** should be higher for non-dominated solutions. The underlying rationale is that the algorithm seeks for non-dominated solutions, which are more relevant than dominated and infeasible solutions, and therefore a more exhaustive analysis is necessary for those solutions. The computation of the (absolute or relative) distance between the images of solution ***x*** according to the scenarios ***s*** and ***s'*** in the objective space, $f^{s'}(x)$ and $f^{s}(x)$, $f^{s'}(x)$ belonging to the ***η***-neighborhood of $f^{s}(x)$, can be done using any metric. The number of parameters required may be reduced by establishing some dependence between them.

6.2 Implementation of the Robustness Methodology for the EBAg Model

The purpose of this section is to present an approach that analyzes whether the non-dominated solutions computed by the hybrid genetic/differential evolution algorithm are robust based on a degree of robustness concept. The assessment of solution robustness is done considering perturbations in the nominal coefficient of the model within a pre-specified range and evaluating the corresponding changes in the objective function space for a given solution structure.

The aim of this robustness analysis is to assess the quality of solutions for different plausible configurations of model data, changes in decision variable values and possibly also parameters controlling the algorithm approach.

The degree of robustness, as proposed in [288,291,320], is based on assessing the effects of perturbations ($\boldsymbol{\delta}$) in the decision variables space and model coefficients regarding the objective function values. The parameter ($\boldsymbol{\delta}$) is associated with the amplitude of the perturbation applied in the non-dominated solution $\boldsymbol{x}$, which is assessed by inspecting successively expanding neighborhoods of possible values.

This perturbation may be assigned to each time slot of the load flexibility aggregated from each cluster by the EBAg.

Figure 58 (bottom) displays the maximum deviation of consumption regarding the daily baseline consumption. This maximum deviation may have: positive values, which correspond to load flexibility representing the amount of load available to decrease the consumption, and negative values, which correspond to load flexibility representing the amount of load available to increase the consumption in each time slot. This maximum deviation considered was [-5%; +5%], since this is a conservative deviation of consumption mentioned in the literature related to behavioral changes influencing energy savings [321].

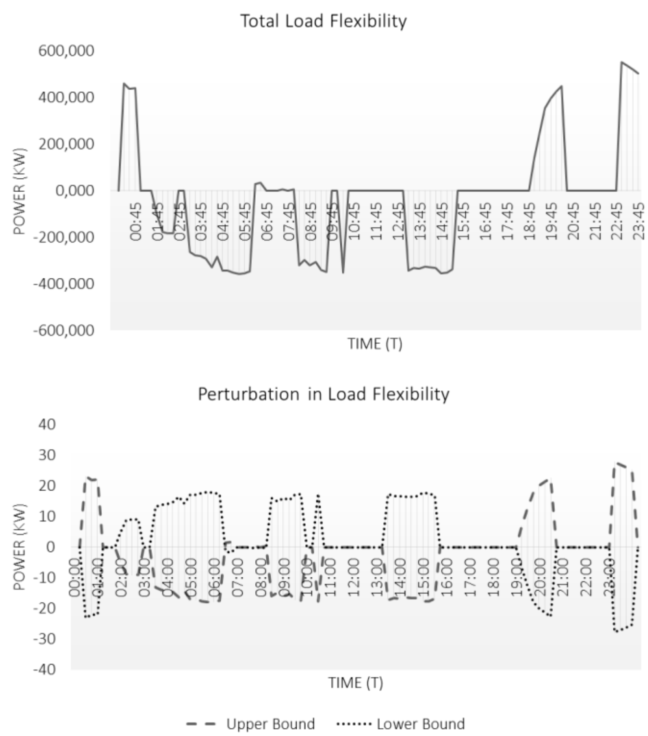


Figure 58 - Load Flexibility gathered and the maximum admissible deviation [δ_t =-5%, δ_t =+5%]

After the execution of the hybrid approach and the identification of the non-dominated front, solutions $(\boldsymbol{x})$ dispersed along this front are randomly selected for the robustness analysis in face of perturbations. These solutions are randomly perturbed in the range [-5%, +5%] in each time slot, thus originating neighbor (perturbed) solutions $(\boldsymbol{x}^{\delta_t})$.

The assessment of the degree of robustness of a solution is based on its behavior around its nominal point, i.e., the position of the selected solution without perturbation and the perturbed solutions derived from the application small perturbations in each time slot. The images of these solutions in the objective function space belong to a pre-specified η-neighborhood degree surrounding ***f(x)***, where η means the level of tolerance with respect to changes in the objective function values regarding to the nominal solution.

The displacement of the perturbed solutions is assessed according to the quadrant, which is centered on the selected solution. In the 1st quadrant (Q. I) and in the 3rd quadrant (Q. III) the solution presents better performance according to one objective function and worse performance for the other objective function; in the 2nd quadrant (Q. II) the solution presents worst performance for both objective functions;

in the 4th quadrant (Q. IV) the perturbed solution presents better performance for both objective functions. The level of the perturbation is progressively enlarged, starting with a random rate bounded in [$\boldsymbol{\delta_t}$ =-1%, $\boldsymbol{\delta_t}$ =+1%] until [$\boldsymbol{\delta_t}$ =-5%, $\boldsymbol{\delta_t}$ =+5%], with an increment of 1%.

The degree of robustness (Figure 59) of the selected solution ***x*** is a value $\boldsymbol{k}, \boldsymbol{k} \in (\mathbf{1}, \mathbf{2}, \mathbf{3}, \mathbf{4}, \mathbf{5})$, when at least 80% of the perturbed solutions belong to the $\boldsymbol{\eta_k}$- neighborhood around ***f(x)***, see Table 6.

Table 6 - Degree of robustness k

$\boldsymbol{k}$	$\boldsymbol{\eta_k}$- neighborhood around *f*(*x*)
1	$\boldsymbol{\eta_1} \in]-\mathbf{0,05}.\boldsymbol{f}(\boldsymbol{x});\ \mathbf{0,05}.\boldsymbol{f}(\boldsymbol{x})]$
2	$\boldsymbol{\eta_2} \in]-\mathbf{0,10}.\boldsymbol{f}(\boldsymbol{x});\ \mathbf{0,10}.\boldsymbol{f}(\boldsymbol{x})]$
3	$\boldsymbol{\eta_3} \in]-\mathbf{0,15}.\boldsymbol{f}(\boldsymbol{x});\ \mathbf{0,15}.\boldsymbol{f}(\boldsymbol{x})]$
4	$\boldsymbol{\eta_4} \in]-\mathbf{0,20}.\boldsymbol{f}(\boldsymbol{x});\ \mathbf{0,20}.\boldsymbol{f}(\boldsymbol{x})]$
5	$\boldsymbol{\eta_5} \in]-\mathbf{0,25}.\boldsymbol{f}(\boldsymbol{x});\ \mathbf{0,25}.\boldsymbol{f}(\boldsymbol{x})]$

The location of more robust solutions on the non-dominated front is a relevant insight to aid the selection of a compromise solution.

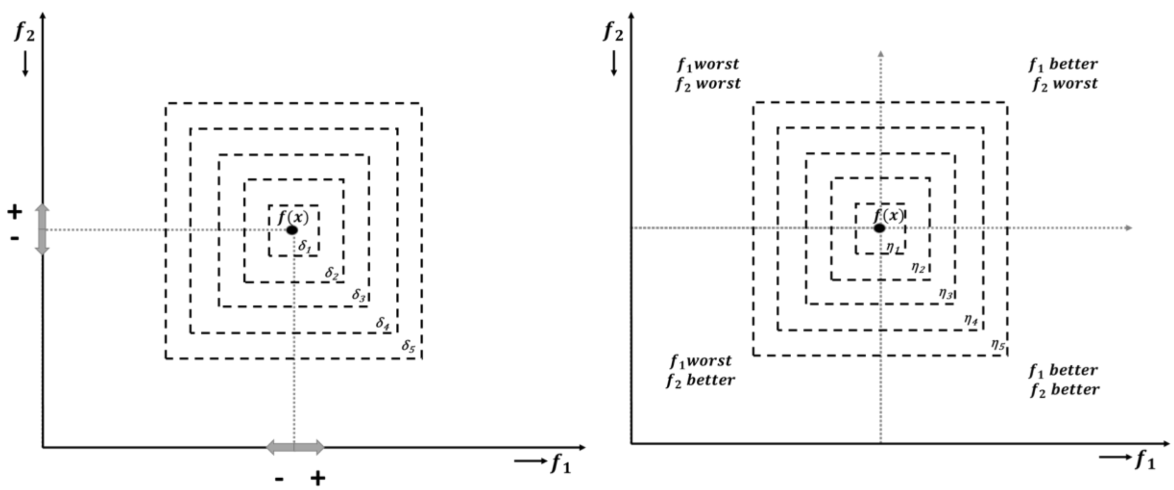


Figure 59 - Representation of the selected solution x, η-neighborhood degree around the nominal solution f(x)

6.3 EBAG ROBUSTNESS ANALYSIS RESULTS

Illustrative results of the computational experiments are herein presented. The Pareto front is displayed in Figure 60, identifying 6 compromise solutions to be subject to perturbations and study their behavior in the objective function space to evaluate robustness.

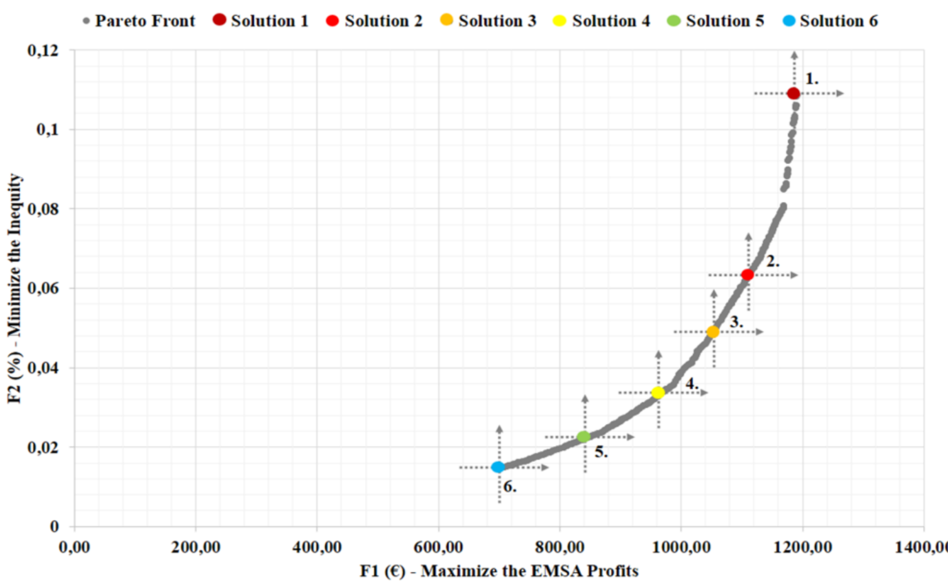


Figure 60 - Pareto front indicating the solution that are subject to robustness analysis

Table 7 displays the maximum deviations (%) of the objective functions for each selected solution when subject to small perturbations in all time slots with respect to the nominal values, i.e., the maximum deviation ($\boldsymbol{\eta}^{max}$) that will be possible to occur when the selected solution is subject to perturbations within the range [-5%, 5%] regarding the load flexibility indeed provided.

Table 7- Maximum deviation in the objective function w.r.t. the nominal situation (%)

	F1	F2*10^4 (%)	F1	F2*10^4 (%)	F1	F2*10^4 (%)
	Solution 1		Solution 2		Solution 3	
δ_t = -1%	-6.08%	-3.00E-05	-6.49%	-4.26E-05	-6.78%	-4.64E-05
δ_t = 1%	6.08%	3.00E-05	6.49%	4.26E-05	6.78%	4.64E-05
δ_t = -2%	-12.15%	-9.00E-05	-12.99%	-1.28E-04	-13.56%	-1.39E-04
δ_t = 2%	12.15%	9.00E-05	12.99%	1.28E-04	13.56%	1.39E-04
δ_t = -3%	**-18.23%**	**-1.00E-04**	**-19.48%**	**-1.42E-04**	**-20.34%**	**-1.55E-04**
δ_t = 3%	**18.23%**	**1.00E-04**	**19.48%**	**1.42E-04**	**20.34%**	**1.55E-04**
δ_t = -4%	-24.31%	-1.20E-04	-25.98%	-1.71E-04	-27.12%	-1.86E-04

δ_t = 4%	24.31%	1.20E-04	25.98%	1.71E-04	27.12%	1.86E-04
δ_t = -5%	-30.38%	-1.50E-04	-32.47%	-2.13E-04	-33.90%	-2.32E-04
δ_t = 5%	30.38%	1.50E-04	32.47%	2.13E-04	33.90%	2.32E-04
	Solution 4		Solution 5		Solution 6	
δ_t = -1%	-7.23%	-5.08E-05	-7.86%	-5.39E-05	-8.27%	-5.59E-05
δ_t = 1%	7.23%	5.08E-05	7.86%	5.39E-05	8.27%	5.59E-05
δ_t = -2%	-14.45%	-1.52E-04	-15.73%	-1.62E-04	-16.,54%	-1.68E-04
δ_t = 2%	14.45%	1.52E-04	15.73%	1.62E-04	16.54%	1.68E-04
δ_t = -3%	**-21.68%**	**-1.69E-04**	**-23.59%**	**-1.80E-04**	**-24.81%**	**-1.86E-04**
δ_t = 3%	**21.68%**	**1.69E-04**	**23.59%**	**1.80E-04**	**24.81%**	**1.86E-04**
δ_t = -4%	-28.90%	-2.03E-04	-31.46%	-2.16E-04	-33.08%	-2.24E-04
δ_t = 4%	28.90%	2.03E-04	31.46%	2.16E-04	33.08%	2.24E-04
δ_t = -5%	-36.13%	-2.54E-04	-39.32%	-2.69E-04	-41.34%	-2.79E-04
δ_t = 5%	36.13%	2.54E-04	39.32%	2.69E-04	41.34%	2.79E-04

The cells in grey indicate that the perturbations applied to the selected solution lead the derived perturbed solution to an inadmissible region (since η>25%). The most common perturbation range that keeps solution robustness is [δ_t =-3%, δ_t =+3%].

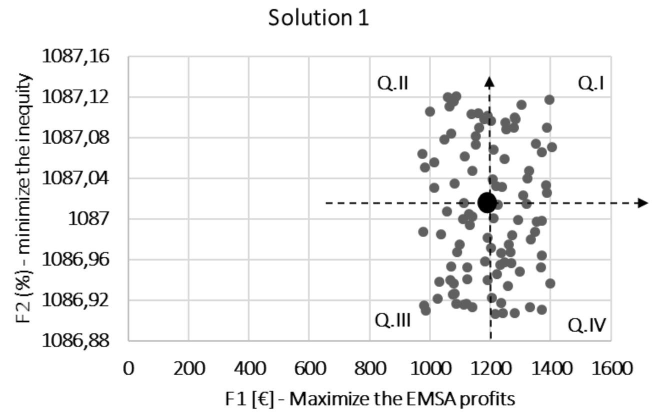
The (nominal) solution selected suffers a random perturbation bounded by [δ_t =-3%, δ_t =+3%] in the 96 time slots of the load flexibility diagram, in order to analyze the degree of robustness of each selected solution. In this way, in the solution selected, a perturbation between [$\boldsymbol{\delta_t}$ =-3%, $\boldsymbol{\delta_t}$ =+3%] will be randomly applied along the load flexibility diagram, to analyze its degree of robustness.

Table 8 presents the maximum and minimum admissible deviation ($\boldsymbol{\eta}^{max}$) in the objective space for each selected solution, its degree of robustness and deviation.

Table 8 - Maximum and minimum values of the objective functions (OF)

Degree	Deviation	F1	F2*10⁴ (%)	F1	F2*10⁴ (%)	F1	F2*10⁴ (%)
	η_t	Solution 1		Solution 2		Solution 3	
	η_t = 0	1 191.58	1 087.01	1 109.77	628.76	1 053.74	491.83
1	ηt = -5%	1 132.00	1 032.66	1 054.28	597.33	1 001.05	467,24
	ηt= 5%	1 251.16	1 141.36	1 165.26	660.20	1 106.43	516.42
2	ηt = -10%	1 072.42	978.31	998.79	565.89	948.37	442.65
	ηt = 10%	1 310.74	1 195.72	1 220.75	691.64	1 159.11	541.01
3	ηt = -15%	1 012.84	923.96	943.31	534.45	895.68	418.06
	ηt= 15%	1 370.32	1 250.07	1 276.24	723.08	1 211.80	565.61
4	ηt= -20%	953.27	869.61	887.82	503.01	842.99	393.46
	ηt=20%	1 429.90	1 304.42	1 331.72	754.52	1 264.49	590.20
5	ηt= -25%	893.69	815.26	832.33	471.57	790.30	368.87
	ηt= 25%	1 489.48	1 358.77	1 387.21	785.96	1 317.17	614.79
		Solution 4		Solution 5		Solution 6	
	η_t = 0	966.33	334.02	841.00	221.33	702.11	149.01
1	ηt = -5%	918.01	317.32	798.95	210.27	659.4	140.0
	ηt= 5%	1014.64	350.72	883.05	232.40	744.8	158.1
2	ηt = -10%	869.69	300.62	756.90	199.20	616.8	130.9
	ηt = 10%	1062.96	367.43	925.10	243.47	787.4	167.1
3	ηt = -15%	821.38	283.92	714.85	188.13	574.1	121.8
	ηt= 15%	1111.28	384.13	967.15	254.53	830.1	176.2
4	ηt= -20%	773.06	267.22	672.80	177.07	531.4	112.8
	ηt=20%	1159.59	400.83	1009.20	265.60	872.8	185.2
5	ηt= -25%	724.75	250.52	630.75	166.00	488.8	103.7
	ηt= 25%	1207.91	417.53	1051.25	276.67	915.4	194.3

Figure 61 to Figure 66 present the results of the analysis done for six solutions (1, 2, 3, 4, 5 and 6), i.e., two extreme solutions (the individual optima of each objective function) and four intermediary solutions. The position of randomly perturbed solutions within the admissible perturbation range is displayed for comparison with the nominal solution (at the center). The dispersion of solutions in each quadrant and the amount of solutions in each *η-k^th^* neighborhood around *f(x),* which determine the degree of robustness, offer information about the expected behavior of the solution when subject to changes.



η_k - neighborhood around f(x)	% of sol	Quadrant	% of sol
$\eta_1 \in \left]-0,05.f(x);\ 0,05.f(x)\right]$	31	Q. I	21
$\eta_2 \in \left]-0,10.f(x);\ 0,10.f(x)\right]$	63	Q. II	25
$\eta_3 \in \left]-0,15.f(x);\ 0,15.f(x)\right]$	86	Q. III	26
$\eta_4 \in \left]-0,20.f(x);\ 0,20.f(x)\right]$	100	Q. IV	28
$\eta_5 \in \left]-0,25.f(x);\ 0,25.f(x)\right]$	100		

Figure 61 - Robustness behavior of solution 1

Solution 1, which is illustrated in Figure 61, presents a degree of robustness of 3, since 86% of the 100 perturbed solutions generated have been allocated between -15%, to 15% ($\eta_3 \in \left]-15\%, 15\%\right]$): 31% of the solutions lie within $\eta_1 \in \left]-5\%, 5\%\right]$; 63% of the solutions between $\eta_2 \in \left]-10\%, 10\%\right]$; 86% between $\eta_3 \in \left]-15\%, 15\%\right]$ and 100% of the solutions perturbed between $\eta_4 \in \left]-20\%, 20\%\right]$.

Therefore, solution 1 is a robust solution of degree 3. According to the quadrants, the solution derived from the solution 1 has been allocated 21% in the Q. I, 25% in the Q.II, 26% in the Q.III and 28% in the Q.IV.

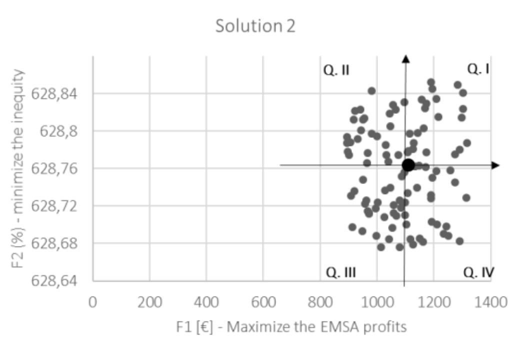
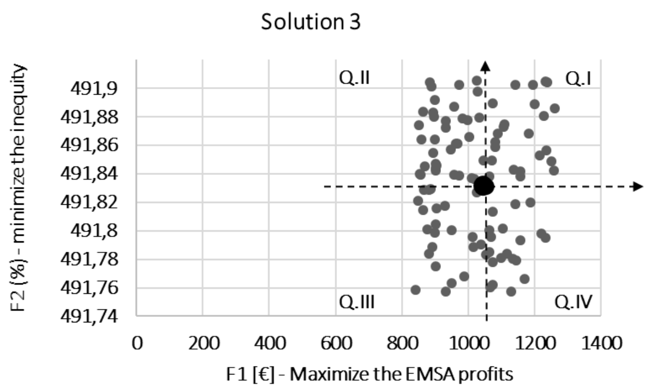


Figure 62 – Robustness behavior of solution 2

Solution 2, which is illustrated in Figure 62, presents a degree of robustness of 3, since 80% of the 100 perturbed solutions generated have been allocated between -15%, to 15% ($\boldsymbol{\eta_3} \in \ ]-15\%, 15\%]$): 32% of the solutions lie within $\boldsymbol{\eta_1} \in \ ]-5\%, 5\%]$; 58% between $\boldsymbol{\eta_2} \in \ ]-10\%, 10\%]$; 80% of the solution between $\boldsymbol{\eta_3} \in \ ]-15\%, 15\%]$; and 100% of the solutions perturbed between $\boldsymbol{\eta_4} \in \ ]-20\%, 20\%]$.

Therefore, solution 2 is a robust solution of degree 3. According to the quadrants, the solution derived from the solution 2 has been allocated 28% in the Q. I, 20% in the Q.II, 31% in the Q.III and 21% in the Q.IV.

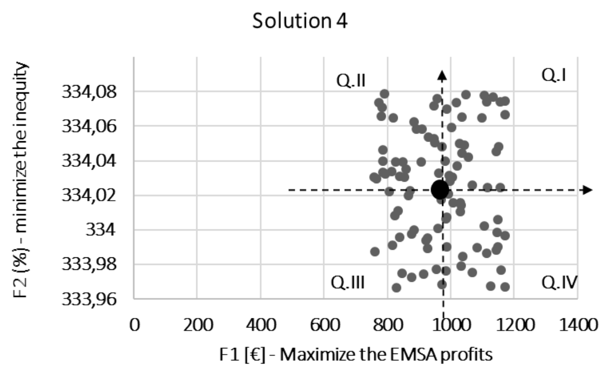


$\boldsymbol{\eta_k}$ - neighborhood around f(x)	% of sol	Quadrant	% of sol
$\boldsymbol{\eta_1} \in \ ]-\mathbf{0,05}.\boldsymbol{f(x)};\ \mathbf{0,05}.\boldsymbol{f(x)}]$	28	Q. I	36
$\boldsymbol{\eta_2} \in \ ]-\mathbf{0,10}.\boldsymbol{f(x)};\ \mathbf{0,10}.\boldsymbol{f(x)}]$	50	Q. II	23
$\boldsymbol{\eta_3} \in \ ]-\mathbf{0,15}.\boldsymbol{f(x)};\ \mathbf{0,15}.\boldsymbol{f(x)}]$	77	Q. III	22
$\boldsymbol{\eta_4} \in \ ]-\mathbf{0,20}.\boldsymbol{f(x)};\ \mathbf{0,20}.\boldsymbol{f(x)}]$	99	Q. IV	20
$\boldsymbol{\eta_5} \in \ ]-\mathbf{0,25}.\boldsymbol{f(x)};\ \mathbf{0,25}.\boldsymbol{f(x)}]$	100		

Figure 63 - Robustness behavior of solution 3

Solution 3, which is illustrated in Figure 63, presents a degree of robustness of 4, since 80% of the 100 perturbed solutions generated have been allocated between -20%, to 20% ($\boldsymbol{\eta_4} \in \ ]-20\%, 20\%]$): 28% of the solutions lie with $\boldsymbol{\eta_1} \in \ ]-5\%, 5\%]$; 50% of the solution between $\boldsymbol{\eta_2} \in \ ]-10\%, 10\%]$; 77% between $\boldsymbol{\eta_3} \in \ ]-15\%, 15\%]$; 99% of the solution perturbed between $\boldsymbol{\eta_4} \in \ ]-20\%, 20\%]$, 100% of the solution perturbed allocation between $\boldsymbol{\eta_5} \in \ ]-25\%, 25\%]$.

Therefore, solution 3 is a robust solution of degree 4. According to the quadrants, the solution derived from the solution 3 has been allocated 35% in the Q. I, 23% in the Q.II, 22% in the Q.III and 20% in the Q.IV.



η_k- neighborhood around f(x)	% of sol	Quadrant	% of sol
$\boldsymbol{\eta_1} \in\ ]-\mathbf{0,05}.\boldsymbol{f(x)};\ \mathbf{0,05}.\boldsymbol{f(x)}]$	28	Q. I	28
$\boldsymbol{\eta_2} \in\ ]-\mathbf{0,10}.\boldsymbol{f(x)};\ \mathbf{0,10}.\boldsymbol{f(x)}]$	50	Q. II	28
$\boldsymbol{\eta_3} \in\ ]-\mathbf{0,15}.\boldsymbol{f(x)};\ \mathbf{0,15}.\boldsymbol{f(x)}]$	67	Q. III	19
$\boldsymbol{\eta_4} \in\ ]-\mathbf{0,20}.\boldsymbol{f(x)};\ \mathbf{0,20}.\boldsymbol{f(x)}]$	93	Q. IV	25
$\boldsymbol{\eta_5} \in\ ]-\mathbf{0,25}.\boldsymbol{f(x)};\ \mathbf{0,25}.\boldsymbol{f(x)}]$	100		

Figure 64 – Robustness behavior of solution 4

Solution 4, which is illustrated in Figure 64, presents a degree of robustness of 4, since 80% of the 100 perturbed solutions produced have been allocated between -20%, to 20% ($\boldsymbol{\eta_4} \in\ ]-20\%, 20\%]$): 28% of the solutions lie within $\boldsymbol{\eta_1} \in\ ]-5\%, 5\%]$; 50% of the solution between $\boldsymbol{\eta_2} \in\ ]-10\%, 10\%]$; 67% between $\boldsymbol{\eta_3} \in\ ]-15\%, 15\%]$; 93% of the solutions perturbed between $\boldsymbol{\eta_4} \in\ ]-20\%, 20\%]$ and 6% allocated between $\boldsymbol{\eta_5} \in\ ]-25\%, 25\%]$.

Therefore, solution 4 is a robust solution of degree 4. According to the quadrants, the solution derived from the solution 4 has been allocated 28% in the Q. I, 28% in the Q.II, 19% in the Q.III and 25% in the Q.IV.

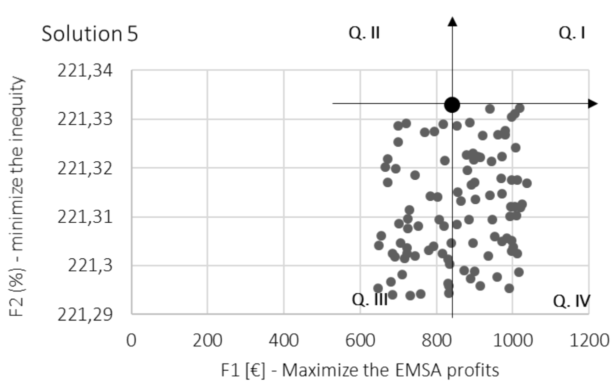
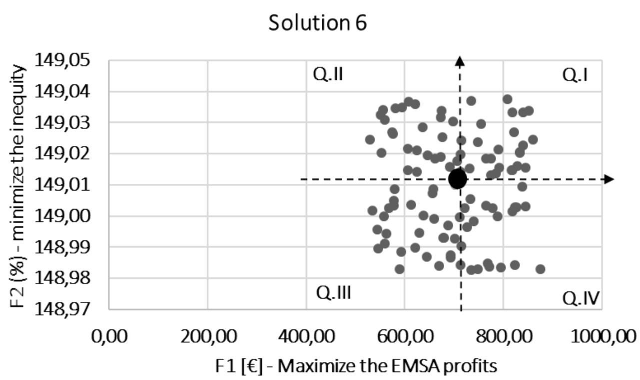


Figure 65 - Robustness behavior of solution 5

Solution 5, which is illustrated in Figure 65, presents a degree of robustness of 4, since 80% of the 100 perturbed solutions generated have been allocated between -20%, to 20% ($\boldsymbol{\eta_4} \in \,]-20\%, 20\%]$): 19% of the solutions lie within $\boldsymbol{\eta_1} \in \,]-5\%, 5\%]$; 39% of the solution between $\boldsymbol{\eta_2} \in \,]-10\%, 10\%]$; 59% between $\boldsymbol{\eta_3} \in \,]-15\%, 15\%]$; 88% of the solutions perturbed between $\boldsymbol{\eta_4} \in \,]-20\%, 20\%]$ and 12% allocated between $\boldsymbol{\eta_5} \in \,]-25\%, 25\%]$.

Therefore, solution 5 is a robust solution of degree 4. According to the quadrants, the solution derived from the solution 5 has been allocated 0% in the Q. I, 0% in the Q.II, 45% in the Q.III and 55% in the Q.IV.



η_k - neighborhood around f(x)	% of sol	Quadrant	% of sol
$\eta_1 \in \,]-\mathbf{0,05}.\boldsymbol{f(x)};\ \mathbf{0,05}.\boldsymbol{f(x)}]$	33	Q. I	24
$\eta_2 \in \,]-\mathbf{0,10}.\boldsymbol{f(x)};\ \mathbf{0,10}.\boldsymbol{f(x)}]$	64	Q. II	33
$\eta_3 \in \,]-\mathbf{0,15}.\boldsymbol{f(x)};\ \mathbf{0,15}.\boldsymbol{f(x)}]$	100	Q. III	31
$\eta_4 \in \,]-\mathbf{0,20}.\boldsymbol{f(x)};\ \mathbf{0,20}.\boldsymbol{f(x)}]$	100	Q. IV	12
$\eta_5 \in \,]-\mathbf{0,25}.\boldsymbol{f(x)};\ \mathbf{0,25}.\boldsymbol{f(x)}]$	100		

Figure 66 - Robustness behavior of solution 6

Solution 6, which is illustrated in Figure 66, presents a degree of robustness of 4, since 64% of the 100 perturbed solutions generated have been allocated between -10% to 10% ($\boldsymbol{\eta_2} \in \,]-10\%, 10\%]$): 33% of the solutions lie within $\boldsymbol{\eta_1} \in \,]-5\%, 5\%]$; 64% of the solution between $\boldsymbol{\eta_2} \in \,]-10\%, 10\%]$; 100% between $\boldsymbol{\eta_3} \in \,]-15\%, 15\%]$.

Therefore, solution 6 is a robust solution of degree 4. According to the quadrants, the solution derived from the solution 6 has been allocated 24% in the Q. I, 33% in the Q.II, 31% in the Q.III and 12% in the Q.IV.

Based on this analysis it may be concluded that solution 1, 2, 3, 4, 5 and 6 present a degree of robustness of 3, 3, 4, 4, 4 and 3, respectively, when subject to small random perturbations around the nominal values. The extreme solutions (i.e. the non-dominated solutions that individually optimize each objective function) present a better degree of robustness in comparison to the intermediate solutions.

6.4 Concluding Remarks

The robustness analysis of non-dominated solutions computed by the hybrid evolutionary approach coupling NSGA-II and DE is based on the degree of robustness concept, taking into account the changes in the performance of the objective function when small perturbations of the model nominal coefficient occur. This section presented the application of this methodology for robustness analysis of non-dominated solutions of the multi-objective optimization model considering maximizing the EBAg profits and minimizing the inequity between the amounts of load flexibility provided by the end-user clusters to satisfy SO requests.

The non-dominated solutions were considered robust until a certain level of perturbation, i.e., until a perturbation [-3%, 3%] is applied in the coefficients of the nominal solutions. In this range, the derived perturbed solutions are considered admissible whenever they lie in the interval *[-0.25. f(x); 0.25. f(x)]* in the objective function space. Solutions out of this interval are considered non-robust. This scenario only happens when the perturbation is higher than ±3% in all solutions obtained in the (nominal) Pareto optimal front.

7. Chapter 7 – Conclusions and Future Work

The setting of the most adequate operating reserve levels is one of the main concerns of the System Operator, mainly due to the integration of a large share of intermittent generation, in order to balance generation and load, assuring both the quality of the service and the security of the supply. The involvement of end-users is a key element for the implementation of demand response as a way to enhance the efficiency of the system infrastructure, also enabling the cope with the intermittency of renewable energy sources. Although the participation of end-users may result in a higher complexity of the system management, it may have a real positive impact on overall system efficiency also contributing to mitigate the volatility of electricity prices.

End-users may become an important element for the provision of ancillary services, by using demand side resources to offer the system operator additional means to enhance system flexibility, robust planning, constraints management and operation scheduling, therefore contributing to the balance between load and supply under a load follows supply strategy.

A comprehensive literature review has been done regarding DR programs and models, including regarding current DR implementations. The experience of aggregators has also been reviewed. This revealed to be an emerging and particularly challenging topic in the context of smart grids. DR strategies can be used to influence end-users and manage demand according to SO requests, the end-users being compensated for their energy consumption behaviour changes and load flexibility provided to be controlled. For making these schemes operational, EMS technologies and infrastructures allowing real-time and bi-directional communication between the grid and the end-users are necessary, in favourable regulatory settings.

This thesis presented the EBAg as a global architecture concept of a system to be connected to individual HEMS in an aggregated level, endowed with optimization algorithms. The EBAg responds to the system operator requests by managing the load flexibility provided by each end-user, considering both profits and the equity of the usage of resources of the end-users involved. The EBAg has the potential to facilitate a load following the supply strategy in a smart grid context, with potential benefits for all the participants involved.

EBAg has a double role: it makes the most of demand responsive loads according to in-house load flexibility, giving incentive and motivating the end-users to change its energy consumption behaviour and it provides system services contributing to improve the system operation, contributing to deal with the increased penetration of renewables which in turn contributes to decreasing environmental impacts and the consequent electricity price variability. The information provided to end-users enables to influence the consumption profile, optimizing the demand profile according to the power system needs.

The optimization model from the EBAg perspective presents multi-objective evaluation aspects (economic and fairness in the usage of resources) of the merits of potential solutions. The model considers the maximization of the EBAg profit and the minimization of the inequity among clusters of end-users, that is, the maximum relative difference between the load flexibility provided by the cluster and the one used by the EBAg, as a surrogated for fairness in the usage of end-user load flexibility. An approach based on a hybrid EA algorithm, making the most of the features of EA and DE, has been developed to solve the EBAg optimization model and to provide hopefully usable solutions in a reasonable computational time. This approach displayed an improved performance, regarding individual EA and DE approaches, to obtain a well-spread and populated Pareto front, able to deal with changes in the input data, SO requests, consumption changes profiles, end-user preferences, restrictions and load flexibility provided, as well as uncertainty in data and parameters.

This research also led to the development of an evaluation methodology to analyze the robustness of non-dominated solutions obtained using the EBAg model and the hybrid EA approach. The non-dominated solutions were considered robust until a certain level of perturbation is applied in the coefficients of the model.

7.1 Future Work

Some future research directions to further develop the EBAg concept are the following:

- The bill savings achieved by the end-user through the local HEMS should be taken into account. For this purpose, it is necessary to work on the connection between the EBAg and the HEMS, including the interaction with the loads.
- Alternative DR strategies, inclusion of storage systems (Electric Vehicle and static batteries) should also be considered.

- Case studies for service buildings or energy communities should be performed.
- Inclusion of robustness analysis in the creation of solutions, that is, operationalized in the computation of the fitness value assigned to solutions.
- Exhaustive analysis of the behavior of the algorithm, based on the variation of the input parameters and the corresponding impact on the solutions.
- Inclusion of real-time prices in the input parameters and real-time preferences of the end-user.
- Application of the EBAg concept in a micro isolated system (namely islands).
- Analysis of the energy consumption behavior of end-users in order to better define the incentive schemes to promote engagement and loyalty, guaranteeing the implementation of the required changes in the load diagram.
- Study of the regulatory frameworks more adequate to enhance the role of the EBAg in the Smart Grid context.

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