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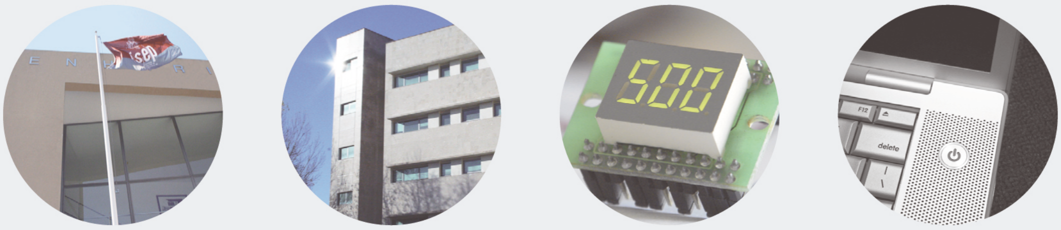

STUDY AND ANALYSIS OF THE USE OF FLEXIBILITY IN LOCAL ELECTRICITY MARKETS

EDUARDO DA ROSA LACERDA

novembro de 2021

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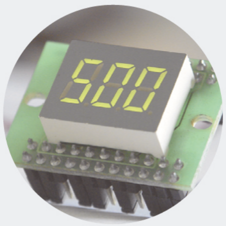


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Eduardo da Rosa Lacerda

isep Instituto Superior de Engenharia do Porto

Departamento de Engenharia Eletrotécnica

Mestrado em Engenharia Eletrotécnica – Sistemas Elétricos de Energia

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Candidato: Eduardo da Rosa Lacerda, Nº 1192196, 1192196@isep.ipp.pt

Orientação científica: Fernando Lezama Cruzvillasante, flz@isep.ipp.pt

Co-orientação científica: Zita Maria Almeida do Vale, zav@isep.ipp.pt

Co-orientação científica: Rubipiara Cavalcante Fernandes, piara@ifsc.edu.br

isep Instituto Superior de Engenharia do Porto

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Abstract

In this work an introduction to Local Electricity Markets (LEM) was done and afterwards evolutionary algorithms (EAs) such as Differential Evolution (DE), Hybrid-Adaptive Differential Evolution (HyDE), Hybrid-Adaptive Differential Evolution with Decay Function (HyDE-DF) and Vortex Search (VS) were applied to a market model in order to test its efficiency and scalability. Then, the market model was expanded adding a network model from the BISITE laboratory and again tests using the evolutionary algorithms were performed. In more detail, first a literature review is done about distributed generation, load flexibility, LEM and EAs. Then a cost optimization problem in Local Electricity Markets is analyzed considering fixed-term flexibility contracts between the distribution system operator (DSO) and aggregators. In this market structure, the DSO procures flexibility while aggregators of different types (e.g., conventional demand response or thermo-load aggregators) offer the service. Its then solved the proposed model using evolutionary algorithms based on the well-known differential evolution (DE). First, a parameter-tuning analysis is done to assess the impact of the DE parameters on the quality of solutions to the problem. Later, after finding the best set of parameters for the "tuned" DE strategies, we compare their performance with other self-adaptive parameter algorithms, namely the HyDE, HyDE-DF, and VS. Overall, the algorithms are able to find near-optimal solutions to the problem and can be considered an alternative solver for more complex instances of the model. After this a network model, from BISITE laboratory, is added to the problem and new analyses are performed using evolutionary algorithms along with MATPOWER power flow algorithms. Results show that evolutionary algorithms support from simple to complex problems, that is, it is a scalable algorithm, and with these results it is possible to perform analyses of the proposed market model

Keywords

Distributed Generation, Demand Response, Evolutionary Algorithms, Local Electricity Markets, Load Flexibility

Resumo

Neste trabalho foi feita uma introdução aos Mercados Locais de Eletricidade (MLE) e posteriormente foram aplicados algoritmos evolutivos (AEs) como Differential Evolution (DE), Hybrid-Adaptive Differential Evolution (HyDE), Hybrid-Adaptive Differential Evolution with Decay Function (HyDE-DF) e Vortex Search (VS) a um modelo de mercado a fim de testar a sua eficiência e escalabilidade. O modelo de mercado foi expandido adicionando uma rede do laboratório BISITE e novamente foram realizados testes usando os algoritmos evolutivos. Em mais detalhe, no trabalho primeiro foi feita uma revisão bibliográfica sobre geração distribuída, flexibilidade de carga, MLE e AEs. É analisado um problema de optimização de custos nos MLE, considerando contratos de flexibilidade a prazo fixo entre os agentes. O distribuidor adquire flexibilidade enquanto que os agregadores de diferentes tipos (por exemplo, os agregadores convencionais de resposta à procura ou de carga térmica) oferecem o serviço. Resolve-se depois o modelo proposto utilizando AEs baseados na conhecida DE. É feita uma análise de afinação de parâmetros para avaliar o impacto dos parâmetros DE na qualidade das soluções para o problema. Após encontrarmos o melhor conjunto de parâmetros para as estratégias DE "afinadas", comparamos o seu desempenho com outros algoritmos de parâmetros auto-adaptáveis, nomeadamente o HyDE, HyDE-DF, e VS. Globalmente, os algoritmos são capazes de encontrar soluções quase óptimas para o problema e podem ser considerados um solucionador alternativo para instâncias mais complexas do modelo. Então um modelo de rede, do laboratório BISITE, é acrescentado ao problema e novas análises são realizadas utilizando algoritmos evolutivos juntamente com algoritmos de fluxo de potência MATPOWER. Os resultados mostram que os algoritmos evolutivos suportam desde problemas simples a complexos, ou seja, é um algoritmo escalável, e com estes resultados é possível realizar análises do modelo de mercado proposto

Keywords

Algoritmos Evolutivos, Flexibilidade de Carga, Mercados Locais de Eletricidade.

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Acronyms

ADS	–	Active Demand and Supply
BRP	–	Balance Responsible Party
DE	–	Differential Evolution
DER	–	Distributed Energy Resources
DG	–	Distributed Generation
DLMP	–	Distributed Local Marginal Price
DR	–	Demand Response
DSO	–	Distribution System Operator
EA	–	Evolutionary Algorithm
ESCO	–	Energy Service Company
ESS	–	Energy Storage Systems
EU	–	European Union
EV	–	Electric Vehicles
FACTS	–	Flexible AC Transmission System
HVDC	–	High Voltage DC
HyDE	–	Hybrid-Adaptive Differential Evolution
HyDE-DF	–	Hybrid-Adaptive Differential Evolution with Decay Function
LEM	–	Local Electricity Markets

LMP	–	Local Marginal Price
PV	–	Photovoltaic
P2P	–	Peer-to-Peer
RES	–	Renewable Energy Sources
TCL	–	Thermostatically Controlled Loads
TSO	–	Transmission System Operator
VS	–	Vortex Search
V2G	–	Vehicle-To-Grid

1. INTRODUCTION

This chapter is intended to provide a quick overview of the topics covered in the dissertation, i.e., the discussion regarding distributed generation, load flexibility, local electricity markets and evolutionary algorithms applied in this context. A brief explanation of the topic is given in Section 1.1, Section 1.2 presents the dissertation objectives, then Section 1.3 presents the contributions of the work and finally Section 1.4 exposes the structure of the document.

1.1. STUDY SCOPE

The increased use of renewable energy sources (RES) has a fundamental role in the search for a more sustainable world. As a result, the development and use of RES have grown exponentially the last decades [1]. In the future, it is expected even more RES participation (e.g., wind and solar power), as well as the incorporation of other distributed resources such as electric vehicles (EV) and heat pumps. This massive integration of resources is changing the electric system and bringing new challenges to the system operators in part due to increased uncertainty in the whole energy supply chain. As a result, it is becoming increasingly complex to control the power flows in real-time and to guarantee stability and reliability of electricity networks [2]. Also, the European Union

(EU) expects, through its objective for energy and climate to 2030, the growth of RES participation of more than 50 % of energy production. This expansion is disturbing the electric system, for example causing congestion problems, demanding a redesign that allows a better predictability and flexibility of resources [3]. In this context of change in the electric systems the study of the best way to integrate the distributed resources and flexibility of the agents involved in the electricity market is of fundamental importance. One of the concepts that aims to best integrate these resources are the Local Electricity Markets, a concept that has been gaining relevance over the years [2]. In this type of market, the integration of local RES is taken into consideration as well as the demand for more active consumer participation in the market, this consumer that often owns its proper generation devices. So, distributed resources, load flexibility and market demands are integrated in the same context in order to solve the problems in current markets [4]. Therefore, the study of viable market frameworks and the definition of ways to perform market clearing are of fundamental importance for the implementation of these models. In this context, this dissertation studies the application of evolutionary algorithms in the market clearing of a proposed market model described in Section 5.1.

1.2. OBJECTIVES

In general, the objectives of this dissertation are to present the concepts and ways of using distributed generation (DG) and flexibility as well as their impacts on the electricity markets. Then, the dissertation aims to present the concept of Local Electricity Markets (LEM), the characteristics that this type of market should contain and finally to perform experiments on one proposed LEM model using differential evolution algorithms described in Chapter 4. So, the objectives of this work are the following:

- Present concepts of distributed generation and flexibility;
- Present the problems that current markets face when adapting to renewable energy resources and distributed generation;
- Elucidate the concept of local electricity markets, possible flexibility services, roles, and interaction between stakeholders;
- Present a brief description of the evolutionary algorithms that are going to be used in the case study.

- Present a market model and perform the market clearing using evolutionary algorithms;

- Then, expand this market model using more aggregators, add a network to the problem and develop a method to evaluate the impacts of demand response in this network;

- Perform the market clearing with the new market topology;

- Test the scalability of the algorithms.

1.3. CONTRIBUTION

The state-of-the-art review contributes to a synthesis of the concepts, main forms of classification, problems to be solved, and ways of solving them regarding the changes caused by the increasing entry of RES into the electrical grid. A brief explanation of the evolutionary algorithms (Differential Evolution, Hybrid-Adaptive Differential Evolution, Hybrid-Adaptive Differential Evolution with Decay Function and Vortex Search) used in the case studies is also given.

The case studies have as contribution the application of evolutionary algorithms to solve the Market Clearing problem in LEM. As well as the expansion of models previously proposed in the literature and analysis of the solutions obtained.

While writing this work a paper about the first Case Study, described in Section 5.2, was written and accepted in the "IEEE Congress on Evolutionary Computation 2021" and is already published. In addition, two papers are being produced, one for a journal, where the case studies 3 and 4 are highlighted, and another for a conference, focusing on the expansion of the scalability test done in case study 2. All the case studies are described in Chapter 5.

1.4. THESIS ORGANIZATION

In addition to the introduction, the thesis has 5 more chapters. Chapter 2 presents the concepts and considerations about distributed generation and flexibility resources and analyzes congestion problems existing in the grid today and possibly in the future.

Chapter 3 presents Local Electricity Market, the characteristics that a market framework should contain as well as possible roles and interactions between stakeholders.

Chapter 4 presents a brief explanation about Differential Evolution, Hybrid-Adaptive Differential Evolution, Hybrid-Adaptive Differential Evolution with Decay Function and Vortex Search.

Chapter 5 presents the case studies simulations and its results, of a Local Electricity Market model simulated in several ways using evolutionary algorithms.

Finally, chapter 6 presents the conclusions about the work.

2. DISTRIBUTED GENERATION AND FLEXIBILITY

Distributed generation is a type of electricity generation characterized by its wide geographical distribution and the proximity of generation and demand [6]. This type of decentralized generation is opposed to the current traditional generation and dispatch models and is becoming increasingly relevant due to the large penetration of RES. These energy sources (Solar Power, Wind Power, etc) come along with the demand for new market models that integrate them in the best possible way as well as the available flexibility of consumers. Thus, this chapter aims to present the concepts of DG and load flexibility, as well as the problems that current energy markets have, such as congestion problems, in order to serve as a basis for the presentation of possible solutions such as LEM.

2.1. DISTRIBUTED GENERATION AND FLEXIBILITY RESOURCES

This sub-section intends to do a short literature review about DG and flexibility resources looking for explain these terms.

2.1.1. DISTRIBUTED GENERATION (DG)

In recent years, there has been a significant increase in the penetration of RES and DG, encouraged due to their environmental and economic aspects [3]. This change will require a fundamental transformation of the energy system, including the redesign of the electricity market, providing greater predictability, linking the wholesale and retail markets, and attracting further investments [3]. In general, the increase of RES in the energy matrix is affected by its uncertainty in generation, since the resources are intermittent, making the conventional energies support still necessary. Consequently, with the largest distributed generation, the returns on investment costs of conventional plants take more time to realize. This situation combined with the DG incentives may cause distortions in the market [4]. So, this changing scenario makes it essential to study the different forms of DG in order to find solutions that optimize their benefits as well as foresee and solve the problems that may arise.

In the literature, there are several ways of defining DG. One of the first articles to explore these different ways of definition was done by Ackermann [5]. Currently a widely used concept is that DG in general refers to the electricity generation on-site or close to the consumption rather than centralized generation which requires large transmission infrastructures over long distances such as large hydroelectric or thermoelectric power plants [6].

The growing liberalization of the energy markets through the years has helped the spread of electricity generation close to the consumers which brings several advantages that, properly exploited, can be of great value to the electricity systems. These advantages are not restricted to the technical part only, economic and environmental aspects are equally benefited when the generation is decentralized [7]. From a technical point of view, when DG is connected to the electric utility's lower voltage distribution lines, energy losses in the transmission lines may be reduced and the network's resilience can be increased. In the economic aspect there are three main advantages: the need for investments in utility generation capacity decreases, costs with generation are reduced as well as the end-users tariffs [7]. Finally, distributed generation has advantages for the environment as it helps supporting the delivery of clean energy and reducing the emission of greenhouse gases such as CO_2 (Carbon Dioxide) and H_2O (Water Vapor) [7-8].

2.1.2. Flexibility Resources And Products

In recent years, the increase in investments in renewable generation (RG) located in the transmission and distribution networks has caused the net demand hourly patterns to change, as well as the consumption patterns. Furthermore, RG increased the degree of generation uncertainty due to the intermittent characteristic of wind and solar sources. These changes pose great challenges to the operation of distribution and transmission networks that need to find solutions to ensure the safety and stability of the electrical system [9]. In this context, the concept of flexibility arises, which is the capacity of a load or generator to change its profile of consumption or generation pattern following a signal of activation or a market stimulus. This is done in order to contribute to the stability of the energy system. The parameters used to characterize flexibility include the amount of power modulation, the duration, the rate of change, the response time and the location [10].

There are three main categories of flexible resources: energy storage, distributed generation and flexible loads [11]. These categories were separated according to their modelling similarities regardless of the technology used. In the first category, related to energy storage, resources are categorized into mobile or stationary storage. Mobile storage refers to the electric vehicles (EVs), which market participation is expected to grow, and Vehicle-To-Grid services (V2G) mechanisms which are expected to provide flexibility to the grid in different points of the energy system. Stationary storage refers to the Energy Storage Systems (ESS) like batteries and pumped-hydro energy storage which are expected as well to have more participation to provide reserve and flexibility services. DG is composed of generators whose electric power output is controlled only by the primary energy source. This group is divided into three distinct categories: Variable Renewable Energy Sources, allusive to solar, wind and small hydroelectric power generation sources; Combined Heat and Power related to energy cogeneration using both electrical energy and thermal energy produced; Conventional Generators, regarding to backup generators and other dispatchables such as biogas. Finally, flexible loads can be categorized into three families, namely: Thermostatically Controlled Loads (TCL), which are loads controlled by thermostats; Load shifting, which are loads that can modify their consumption period, i.e., some domestic objects and industrial processes; Curtailable Loads, which are loads that can reduce their consumption in a given period [9,11]. Figure 1 illustrates the previous explained flexible resources categories.

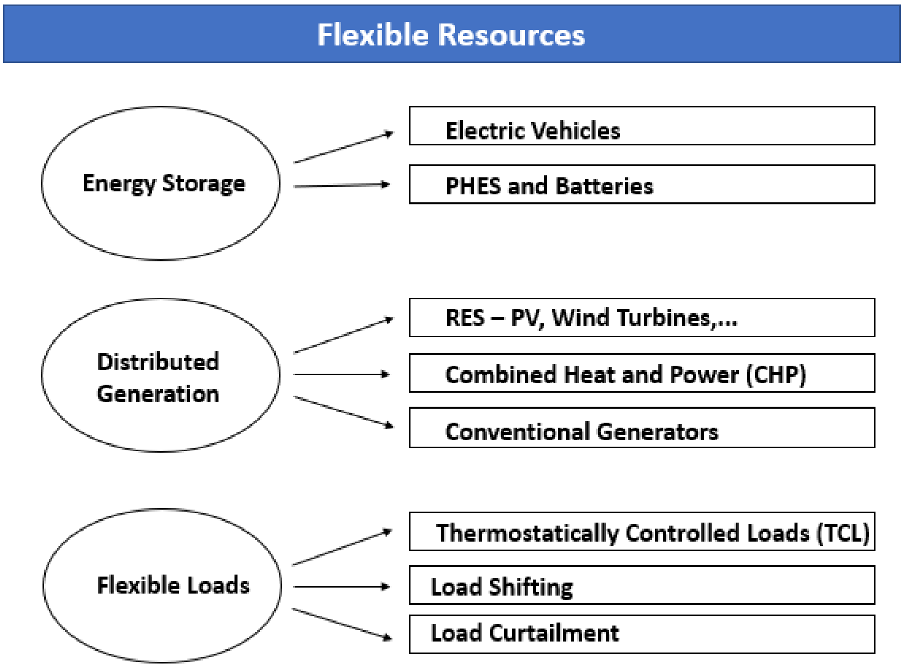


Figure 1 – Flexible resources categories

RES are not fully integrated into the current energy markets [9]. The mechanism of feed-in tariffs is still currently used to remunerate renewable energy generators. This form of operation makes it necessary to generate flexibility incentives, causing market distortions [12]. Another problem caused by the growing participation of the DG is in the operation of transmission and distribution networks. Energy balance and frequency control are the biggest problems observed in transmission networks [9]. As a result, it becomes necessary to guarantee the ramping availability of generators aiming to solve these problems. At the distribution grid, reverse power flows, congestion and voltage issues are the main problems caused by DG penetration [9]. Therefore, it becomes necessary to transform flexible resources into flexibility products and services with the objective of integrate them into the market and remunerate them. The demand by grid operators for flexibility services is significant due to their need of solving their energy management problems, optimizing their operation and decreasing the investments [9,12].

2.2. Distribution Network Congestion Management Solutions

The main function of an electric power network (Figure 2) is the provision of active power to consumers in an efficient, reliable, and quality manner [13]. In the context of the large penetration of RES, network congestion problems may happen, with the voltage problem (the limit of ±5% in the bus voltage being disregarded) and the overload problem (the load close to the thermal capacity of the system components) the more serious problems to be solved [13]. The voltage problem can happen due to active and reactive power losses in the lines related to resistance and reactance, or even due to the distributed generation of RES that could generate over-voltage problems in some busses. Because of DG penetration, reverse power flows are another problem that demands solution. This reverse flow, in addition to the normal power flow, may contribute to the resulting power flow being higher than the limit of the system components and cause overload [13].

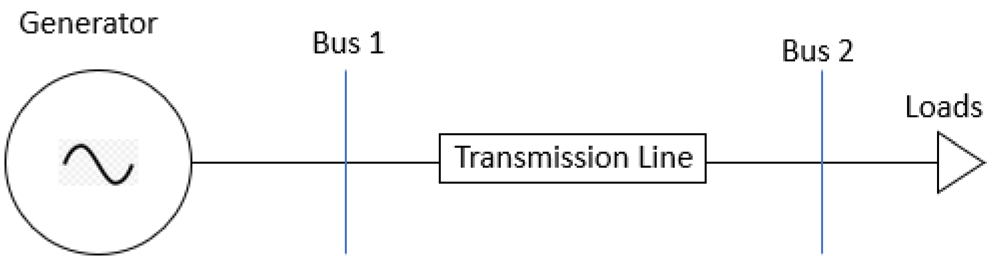


Figure 2 – Electric power network simple illustration

Since the reliable provision of electrical energy is essential, network operators use different types of methods to ensure this prerogative. These methods are divided into two groups:

- **Direct methods**: When the network operator takes concrete actions to solve the issue, such as strengthening the network, active and reactive power control, load shedding or utilize FACT devices as described in Sub-Section 2.2.1;

- **Indirect Methods**: Market mechanisms that encourage changes in demand for electricity as described in Sub-Section 2.2.2.

The methods can be used separately, however the use of both in a hybrid way is the most common [13,14].

2.2.1. Direct Methods

Direct methods, as the name suggests, are methods adopted by the Distribution System Operator (DSO) or Transmission System Operator (TSO) whose application directly causes the desired effect. These are applications where operators have direct control and the application-effect relationship is direct. The more conventional direct methods are the network reconfiguration, grid reinforcement, reactive power control and active power control [4].

Network reconfiguration is the selection of the proper topological structure of the network for minimum load balancing index by changing open /closed status of sectionalizing and tie switches [15]. This method is applied aiming the delivery of power to consumers in a more efficient and suitable way without changing the radial structure of the network [13]. The authors of [15] present a radial distribution system reconfiguration problem for load balancing and solve it using genetic algorithms. Meanwhile in [16] the authors combine network reconfiguration and DERs scheduling in their congestion management strategy in order to enhance distribution system resilience. Other methods to tackle the congestion management problem are the grid reinforcement, which means changing the physical characteristics of the existing network in order to increase its capacity [17], as well as the investments in new DG. However, these are long term methods that require a higher investment. Thus, it is necessary applying the active management of DSO-network and DERs if possible, to avoid such high investments [18].

In addition to the other direct methods mentioned above, another widely used mechanism is the active and reactive power controls on the buses. The authors of [18] explain some already used mechanisms for active and reactive power control being them power electronics-based solutions like flexible AC transmission systems (FACTS) and high voltage DC (HVDC) as well as on-load tap changing transformers and phase-shifting transformers as feasible options to manage the power flow. The authors of [19] discuss with detailing the application of HDVC and FACTS highlighting the advantages of using these methods, like the improvement of the dynamic conditions in AC systems and transfer capability for HDVC and improving real power transfer capability in the lines, prevention of sub-synchronous resonance oscillations and damping of power swings for FACTS.

2.2.2. Indirect Methods

Indirect methods for solving network congestion problems are based on market mechanisms such as price signals or contracts that manipulate the energy demand of consumers offering economic benefits to participants. The indirect methods most used in the literature refer to distributed local marginal price (DLMP) [20], dynamic pricing, local peer-to-peer electricity markets and local electricity markets [4]. These are market-based methods which implementation can maximize social welfare, cause least discomfort to customers and encourage more participation of the end-users in the energy planning [21].

One of the broadest and most frequently used concepts when market methods are mentioned in solving network congestion problems are local marginal price (LMP) markets. In this type of market, the energy price varies according to the location and the cost of delivering an additional unit of energy to the grid, extending this concept to the distribution networks, DLMPs arise in which the DGs are properly remunerated in the case of increased energy production in the period in which the local buses present congestion [21]. In this market, the concept of dynamic tariff also appears, considering that the demand for energy is price-sensitive the price of energy responds to this demand in order to reduce consumption and avoid congestion. The authors of [21] present a DLMP model where the DSO calculates dynamic tariffs and publishes them to the aggregators, who make the optimal energy plans for the flexible demands. The authors of [20] introduce a method where EVs are used in a DLMP as DER to reduce network congestion. The authors of [22] present the definition and types of dynamic tariffs commonly used in energy markets as well as the proposal of a daily dynamic tariff structure.

In recent years, with the development of different studies, the need to formulate new models and market structures that more effectively integrate the DER, the available flexibility and the demand for a more active role of consumers in the energy markets has been identified [4]. Traditionally, there are centralized energy markets where consumers are grouped in large areas, commonly the geographic limits of a country, and the control of energy supply is operated centrally using large power plants. However, with the penetration of DER, decentralized market models have been proposed where small-scale generators are located where their produced energy is consumed. Microgrids stand out in decentralized markets where prosumers and consumers trade energy locally through a platform with their community [23]. This model promotes consumption close to generation, efficiency in the use of resources and, consequently, sustainability, since it reduces the need for energy transport over long distances, decreases the latency in managing network problems and strengthens the local community by encouraging reinvestments in RES. With the advancement of information technologies, new proposals are made for better execution of these microgrids [23]. A recurring proposal refers to peer-to-peer local electricity, where the application of blockchain technology would ensure, in a decentralized manner, the security of this market, the resolution of conflicts of interest and the use of smart contracts. In addition, the main advantage of using the blockchain is transparency, as with this technology the distributed and secure transaction log allows for complete and continuous tracing of even the smallest energy transactions. [23]. The authors of [23] designed a blockchain-based microgrid energy market without the need for central intermediaries, evaluated it as a case study based on seven components and identified that it fully satisfied three and partially fulfilled an additional three of the seven components.

Finally, there is a more robust proposal for adapting electricity markets, which refers to LEM, due to the fact that they can be adapted to the current wholesale market with some adjustments to the current framework [4]. The author of a LEM book [24] established the following definition for LEM:

“A local electricity market is a market platform for trading locally generated (renewable) electricity among residential agents within a geographically and socially close community. Security of supply is ensured through connections to a superimposed electricity system (e. g. national grid or adjacent local electricity markets).”

In this type of market, consumers become active participants, being able to exchange energy locally having as a guarantee of supply a backup system (i.e national energy system) [25]. LEM resolves potential conflicts of interest between DSO and TSO that may occur and facilitates the use of DER [4]. The authors of [25] conducted a literature review on the concept of LEM discussing current works in the area and identifying gaps in the literature.

2.3. FINAL REMARKS

Based on the literature review, it can be seen that with the large introduction of RER and DG into the energy matrix challenges arise. Among these challenges there are problems related to congestion management, voltage and grid losses.In order to solve this type of problem there are direct and indirect methods, LEM being one of the indirect methods. LEM aims to integrate DG, load flexibility and more active prosumer participation in the same framework in order to use its potential being one of the possibilities of market model renewal that has been studied.

3. LOCAL ELECTRICITY MARKETS

In view of the growing desire for the active participation of final consumers in the electricity market and the continuous increase in use of RES for electricity generation , it is necessary to study the proper incorporation of these new decentralized agents in the energy system. Due to the proliferation of digital technologies, network automation and inevitable changes in the roles of stakeholders in the market, a promising idea to aid this change are the so-called LEM, which proposes to extend to a local level the existing liberal wholesale markets present in Europe and United States [26]. So, this chapter intends to present the concept of LEM, its related challenges, prerogatives and Stakeholders.

End-users with low demand or generation capabilities are often excluded from the bidding process due to various legislative restrictions and the top-down pattern of markets where larger producers and industry bodies actively make decisions while end-users are reactively involved in the market. One of the purposes of LEMs is to solve this problem by providing residential actors market access utilizing a market platform [25]. This growing demand for the empowerment of the end-consumer of electricity is linked to the increase in information and its growing participation in the market when they generate solar energy, store energy in batteries and exchange energy from their own electric car with the system

(V2G). The intention for greater empowerment and participation in the market of these consumers is the desire to reduce energy costs, greater freedom, independence from the government and the protection of the environment [26-27].

As mentioned before, the insertion of DG and RES in the system generates uncertainties regarding energy production, and with it, brings challenges regarding the balance of supply and demand. Furthermore, network problems, such as reverse power flows, line losses voltage deviations linked to these changes were mentioned in Chapter II. However, in addition to these changes in consumption patterns, a large increase in energy demand is expected at the same time in the next few years, related with the introduction of electric cars and space heating by heat pumps[3]. These trends offer excellent opportunities for flexibility as vehicle loading and space heating behavior can be adapted during the day following market incentives. In addition to this, the use of electric vehicle batteries as energy storage and V2G are unique opportunities for reducing system power peaks and reducing costs by limiting capacity usage [3]. Energy conversion technologies such as power-to-gas and fuel cell units are also standing out and becoming viable options for the energy market. Taking this into account, energy markets need to adapt to the new reality, aiming at the integration of all stakeholders and new forms of energy in a decentralized manner, so that each participant can compete and profit according to their contribution [3]. In this context, the study of the implementation of LEM aims to solve these integration issues without changing the standards of quality and safety in energy supply [3].

Similar to the wholesale market, LEM do not act independently and need to be connected to a larger system i.e., backup system, in order to guarantee the security of supply [25]. As pointed out by [26], there are three main topologies to study the interaction of agents and market models, namely, the interactions between agents arranged in a peer-to-peer way (directly between agents), pool-trading (indirectly, through aggregation) or in a hybrid way. The study in [28] explains these different interaction proposals as well as their advantages and disadvantages. A further explanation of these type of markets is conducted in Section 3.1.1.

The implementation of LEM is not dissociated from several challenges that arise for the system to be effective, safe, and viable. The article [26] highlights, among these challenges, 5 crucial factors that must be studied in the establishment of LEM, Table 1 presents these factors and some of the challenges related to them. Taking this into account it, is seen as necessary to implement a legal framework that addresses all present and future changes and challenges in the energy systems.

Table 1 – LEM Challenges [26]

Factor	**Related Challenges**
Optimal utilization of distributed supply	- Changes in line losses, voltage levels and power quality. - Reduction in system reliability and consequently more need for flexibility. - Increase of computational complexity. - Potential waste of resources.
Optimal utilization of demand response	- Increase of computational complexity. - Forecast of individuals are error prone. - Similar tariffs might lead to different outcomes locally.
Efficient and secure operation and technical implementation of localized markets	- Risk of increasing electricity costs. - Scalability issues of communication devices. - Reliable solutions for metering without a centralized authority.
Existing and emerging legal boundaries	- Relationship with existing markets. - Stakeholders in current markets might be against these new changes.
Socioeconomic aspects and human interaction	- Encouragement of participation. - Security of information data.

	- Dealing with conflicting stakeholders interest.

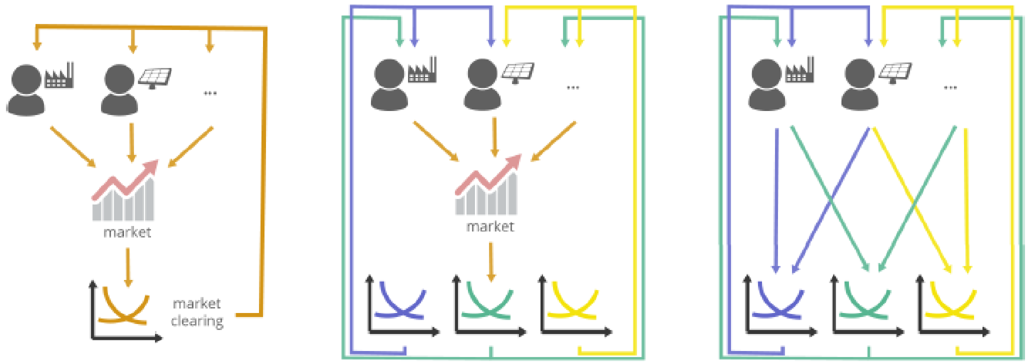
3.1. LEM Required Prerogatives

In order to implement a framework for local energy markets, attention must be paid to several aspects and identify how various interactions will be carried out in the market so that it does not have gaps to fill, and the framework is usable. In the literature reviews [4] and [26], several LEM proposals were studied and patterns and shortcomings in the models were identified. From that, some prerogatives that must be presented in the elaboration of a LEM framework were identified, being them:

- Market Topology;
- Services Definition;
- System Level and TSO-DSO Coordination;
- Unbundling Principle Respect;
- Rebound Effects;
- Stakeholders.

3.1.1. Market Topology

In a literature review [26], regarding LEM, there are 3 topologies of market side interactions identified by: Pool Market Trading, Hybrid Market and Full P2P. In Figure 3, taken from [26], these market topologies are shown.



[1]

Figure 3 – LEM clearing topologies (Pool Market Trading, Hybrid and Full P2P) [26]

A Full P2P Market is characterized by the direct transaction of an amount of energy at a certain price without the supervision of a centralized body [28]. In this type of system, the distribution operator would be remunerated at a management fee tariff according to the type of service and the distance between buyer and seller [27]. Its main advantage is the empowerment and greater freedom offered to consumers who can buy and sell their energy according to their preference (cost, sustainability, etc.). For this type of market to be available some challenges must be overcome as a high computational capacity is required, the slow convergence in the market consensus process and the uncertainty regarding the energy balance that makes it difficult for grid operators to guarantee the security and quality of the energy supply [28].

Pool Market Trading or Community-based market is a model where there is a community manager or aggregator that manages the energy exchanges within the community in a centralized manner, in addition this is responsible for interactions with agents outside this market. The main advantage of this market model is to facilitate the interaction between agents that pursue the same objective. Through the aggregator they can access the external market in a joint manner and buy/sell energy and flexibility services. In addition, the computational infrastructure required is lower than the P2P markets, however

[1] DOMINOES is a European research project supported by Horizon 2020 and developed by Enerim (coordinator – Finland), E-REDES (CNET and EDP Distribution), ISEP (GECAD), Lappeenranta University of Technology – LUT (Finland), VPS (UK), University of Leicester – UoL (UK), and University of Seville (Spain). Available: http://dominoesproject.eu/

the freedom granted to the end-user is much lower and the aggregator's handling of consumer expectations is likely to be frowned upon [28].

The third type of marketplace discussed is Hybrid P2P, which is the middle ground between the two topologies presented above. The model is divided into two levels: at the lower level, aggregators control their customers' loads and from these loads offer products to the upper level, where they can exchange not only with system and market operators but also with other aggregators. This topology is the most compatible with the electrical system in the coming years since its scalability regarding the computing infrastructure, the greater predictability of the grid operators and because it is a junction of the best aspects of the previous models [28].

3.1.2. FLEXIBILITY SERVICES DEFINITION

A fundamentally important issue for the adequacy of a LEM framework is the elaboration of flexibility services available in the market, and the elaboration of flexibility standard products, with well-represented stochasticity, so that they can be bought and sold. These standard products should be well defined so that the market formulation is more precise, so the roles and responsibilities assigned to each stakeholder are properly respected [4]. The flexibility services sought by each stakeholder are different, for example, the flexibility needs of the DSO are different from the needs of the TSO [12]. Therefore, the flexibility products for each of them are different and should be considered when designing a framework.

DOMINOES, a research project about local energy markets, has listed the following parameters that should be defined when defining a flexibility product [29]. These are:

- Period (Time Window);
- Probability of Availability;
- Location (Node location or grid metering point);
- Constraints on Ramp Rate (Maximum Increase or Decrease);
- Activation Delay (s);
- Active or Reactive Power;

- Type of control;
- Cost of Activation and Cost of Availability;

Table 2 presents some of the flexibility services defined and their beneficiaries (TSO, DSO or Balance Responsible Party (BRP) in two frameworks that are already very well structured, namely the Danish project EcoGrid 2.0 [4] and the U.S.E.F Framework [3].

Table 2 – Potential Flexibility Services [3,4]

Potential Beneficiary	Service
DSO, TSO,BRP	Load Increase
DSO, TSO, BRP	Load Decrease
TSO, BRP	Balance Service
DSO	Voltage Control
DSO	Power Limitation
TSO	Primary, secondary and tertiary control
DSO, TSO	Controlled Islanding

3.1.3. REBOUND EFFECTS

Rebound (or recovery) effect is a characteristic of certain types of loads, such as direct electrical heating and heat pumps, that when they are reduced, there is an opposite effect immediately afterwards so that they return to their original state. Thus, the rebound effect is characterized by an increase in energy consumption immediately after a reduction or a reduction prior to the increase in consumption. As an example of this type of load we can cite the heat pumps in office buildings, if in a DR program it can be forced off one period, but after that it must increase its consumption so that the temperature of the environment returns to normal. The aggregators of this type of load must consider this effect when selling flexibility services, having therefore to inform the rebound power as well as the duration [32] when selling the service. Figure 4 exemplifies this effect. P_s and

d_s are the response power and duration while P_{rb} and d_{rb} are the rebound power and duration respectively.

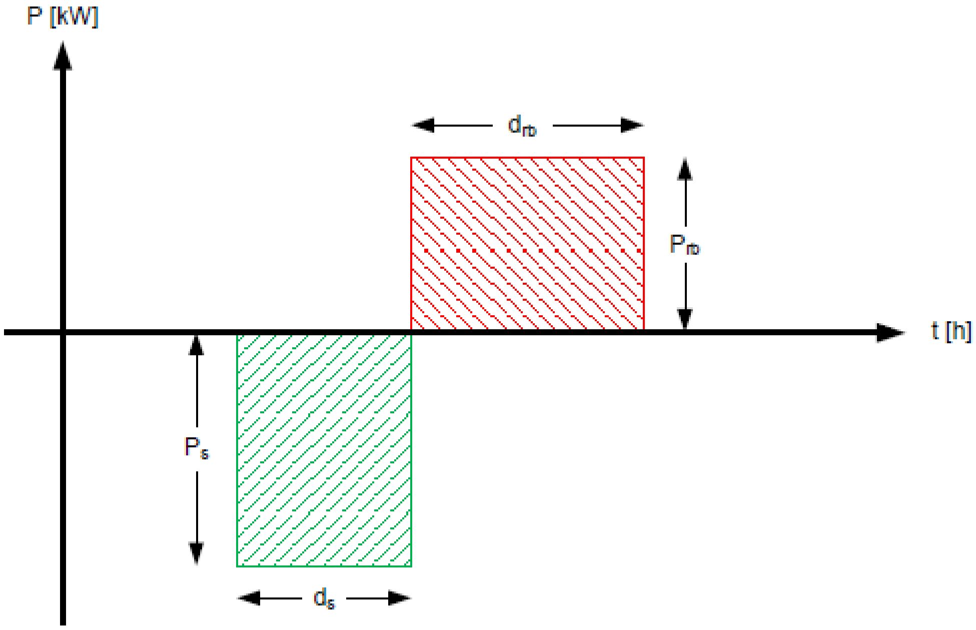


Figure 4 – Rebound Effect [32]

In order to model the ability of a load with rebound to provide DR to the system [37] introduces the concept of asymmetric block, a representation where the rebound and the response are modeled in blocks, which are not necessarily equal. The study of thermostatic systems and their possible use in the creation of flexibility services is of great value, in [38] the complex behavior of refrigeration machines was studied and modeled ways of using its rebound in flexibility services, in this study it was found the feasibility of using this form of flexibility as well as the asymmetric behavior of the rebound in relation to the response used. The study [39] compares several ways of modeling the rebound effect and its possible financial impacts on the agents that use this resource.

3.1.4. System Level, Unbundling Principle and Other Assumptions

When designing a market framework several prerequisites must be defined in order for it to operate adequately. The rebound effects, market topology and services definition were explained in the previous subsections, however there are other definitions of paramount importance in the context of LEMs, being them [32]:

- **System level:** The targeted level of the market must be defined. Distribution, transmission or both levels may be the target for the exploration of flexibility. Many times the needs of the DSO are not sufficient to drive a market, so the ideal scenario is the DSO, TSO and BRPs participation in the same market;

- **TSO-DSO Coordination:** Services provided to the DSO, BRPs and TSO affect directly each other so the market framework must ensure that the use of flexibility is coordinated among these agents to avoid system instability;

- **Unbundling Principle:** Network operation and market activities must be separated, TSOs and DSOs cannot own power generation or consumption units [32];

- **Services Conditions:** The basic characteristics of the services are needed, so the market type utilized such day-ahead-market and reserve market must be defined;

- **Aggregators Action:** It must be defined if more multiple aggregators can operate within the same household as service providers or if the management of a consumer is exclusive to the aggregator. Another important consideration is that customers must be able to choose and switch between aggregators freely to ensure market competition;

- **Market Periods:** The definition of the market periods is a basic definition a framework must define. The services periods are defined following this definition;

- **Data Security:** Secure technology of information systems are required in order to protect the privacy of each stakeholder involved in the market.

These are the main prerogatives that are required to ensure the elaboration of a functional LEM framework. Other prerogatives may appear depending on the context of the local where the LEM is implemented.

3.2. STAKEHOLDERS

In the LEM context, new participants enter the market as well as new products are added, so the market mechanism and the interaction between the agents must be defined, defining the roles of each stakeholder, the flexibility products they can offer and the interaction between each of them is important when studying a possible framework for implementing an LEM.

3.2.1. AGGREGATORS

Aggregators act as intermediaries in the negotiation of flexibility in the energy market, this new player exploits the flexibility of its customers in order to make it tradable and be able to solve problems of system operators as well as provide balancing services [29]. In fact, these aggregators accumulate flexibility from their customers (residential, commercial and industrial) through DR programs. This flexibility from each individual customer is added to a joint pool and from this pool is transformed into flexibility products with considerable volume and value to different stakeholders of the system.

This way of acting is important to the market because the aggregation of individual flexibilities mitigates the risks of both the aggregators and their clients. For example, if the flexibility depended on only one source, the non-delivery of the service would not happen as planned and the flexibility product would not be delivered, resulting in losses to the aggregator and the system. In addition, prosumers also mitigate their risks by not participating directly in the market and being exposed to large price variations; instead, they participate through contracts with aggregators that, by gathering several loads, can offer better conditions to their clients. Thus, aggregators are essential in the implementation of DR programs for the sake of aggregate and turn this flexibility into a unique resource. In the implementation of a framework for LEM it must be considered that several aggregators must enter the market and that their entry must be standardized and certified. For them to enter the market it is important that they have a deep knowledge of the area and the consumption profile of their customers, so that they can fully exploit the flexibility that the customers themselves don't even know they have. In addition, the information technology needed for data transfer and demand control by the aggregators is of fundamental importance [30].

Aggregators have four potential customers, these are the Prosumers, the Balance Responsible Party (BRP), the TSO and the DSO. For prosumers the approach refers to traditional DR programs while for the other three options the aggregate of the flexibility that aggregators have in their portfolio can be turned into a product and negotiated with these stakeholders. Therefore, the aggregator and the prosumers agree on commercial terms and conditions of control of the Active Demand and Supply (ADS) asset by the aggregator, which optimizes the value of the flexibility by selling to where there is demand combined with the highest price [29].

In LEM these participants must establish contracts with the aggregator aiming to define the flexibility activation criteria. These contracts, which, according to the framework, can be renewed periodically (weekly, monthly, etc.) settle the activation price as well as the allowed activation period and number of times per day. That is, in LEM the contracts [31] are introduced:

- **DSO-Aggregator Contract:** Contract between DSO and aggregator that defines the type and amount of flexibility contracted, the price of the service, the activation criteria, the responsibilities of each stakeholder, the required information exchanges and the contract time;

- **TSO-Aggregator Contract:** Contract between TSO and aggregator with the same criteria as the DSO-Aggregator Contract;

- **BRP-Aggregator Contract:** Contract between BRP and aggregator with the same criteria as the DSO-Aggregator Contract, but with flexibility services related to imbalance solution;

- **Prosumer-Aggregator Contract:** Contract between prosumer and aggregator that must define the flexibility reserve, activation price, allowed activation periods, and fines in case the contract is not fulfilled.

3.2.2. PROSUMERS

The continuous progress in the integration of DG and information technology is helping to turn more and more energy consumers into prosumers [28]. Prosumers are small-scale residential, commercial, or industrial consumers who not only demand but also produce energy through PV panels and wind turbines. These consumers want to participate more actively in the market so that they can receive benefits related to the energy they produce in order to reduce costs, increase profits, increase autarchy, increase the share of local/green RES [24]. In this way the energy generated by prosumers can be consumed locally as well as exchanged in the local energy market, evolving from a passive to an active player in the market. This stakeholder has also the characteristic of being more aware of the efficient consumption of energy willing to participate in demand side management programs in order to obtain financial savings when optimizing their energy consumption [29].

The participation of prosumers happens through ADS devices that respond to price and other signals from the aggregator and provide flexibility services to the system. In this way, the prosumer owns the ADS device and authorizes its control by the aggregator, establishing limits that do not compromise their comfort level, but that can generate profits for both parties. However, before offering flexibility to the market, the prosumer can use its own flexibility for in home optimization [3], such as Table 3:

Table 3 – Flexibility services for the Prosumer [3]

Service	Description
Time of use optimization	Optimization based on changing energy consumption from a period when the tariff is expensive to periods when the tariff is lower.
Control of maximum load	Control established by contract of the maximum load that a consumer will be allowed at any given time.
Self-Balancing	Optimization in the purchase and sale of energy (energy from local generation) in order to maximize profits.

Thus, the inclusion of these actors in the market stimulates the economic growth of the region as well as greater energy use since prosumers can trade self-produced electricity and use the full potential of DER [29].

3.2.3. DISTRIBUTION SYSTEM OPERATOR

The DSO is responsible for the free flow of power between suppliers and customers in a stable and cost-effective manner [3]. The demand for electric power is growing over the years and with the arrival of electric vehicles the tendency is for it to continue to grow. Thus the grid capacity must be sufficient to accommodate this increase in load. One of the alternatives is to invest in increasing grid capacity and building new lines, but this is a long-term solution that requires a lot of capital. Another alternative is to use flexibility in order to reduce the load in critical periods and avoid expansion costs, LEM offers this option by using flexibility services that help the DSO to manage the network[3]. Therefore, it is important to identify and add flexibility services to the energy market so that the grid can continue to provide its current levels of stability, security and reliability [3]. As these products are added to the market, the DSO's role will be to identify their problems and formulate service requests in the market according to pre-established product standards [32]. It is important to point out that the DSO should not publish its grid status for privacy and security reasons, but only to request specific services from aggregators that do not know the grid boundaries. It is also important that the aggregators inform their operation plans to the DSO in advance, so they do not cause unexpected disturbances [31].

The analysis of the value of the available flexibility so that the DSO can use it in the best way is the subject of studies and debates among the involved stakeholders [33]. With the identification and definition of standardized products, this analysis becomes easier to perform. For the DSO, some flexibility services that the aggregator can offer so that flexibility is explored were identified in Table 4 [3]:

Table 4 – Flexibility services for DSO [3]

Service	Description
Congestion Management	Reduce peak loads with the purpose of avoiding thermal overload of the system components.
Voltage Control	Increasing the load or decrease the generation is an option to avoid exceeding the voltage limits.
Grid Capacity Management	Use load flexibility aiming the optimization of the operational performance extending the components lifetime and reducing grid losses.
Controlled Islanding	Avoid supply interruption in a given grid section.
Power Quality Support	Aggregator might provide equipment to the prosumers which are technically capable of improving grid´s local power quality and sell it as a service to the DSO.

3.2.4. TRANSMISSION SYSTEM OPERATOR

It is the responsibility of the TSO to guarantee the free flow of power on the transmission lines that connect the generators to the end-users in a way that guarantees the stability and security of the system. In order to do it and keep the generation and consumption equilibrated TSO manages the congestion in the lines and network constraints administrating energy losses providing ancillary and balancing services [29]. The intermittent character of new energy sources makes continuous optimization of energy dispatch necessary, since generation in many different locations causes the power flow to change constantly with little predictability. This change in patterns as well as the large increase in demand (for instance, caused by EVs) may generate problems for the TSO that can be alleviated if more flexibility services are available. In the current model, the flexibility demanded by the TSOs is supplied by large energy generating units that are available to increase or decrease generation according to the TSO's signals. However, with the advent of DG, large generating units are decreasing compared to small-scale units. This shift changes the way flexibility is made available to the TSO, which now must also demand this service from several small market agents [3].

The flexibility products available to the DSO can be categorized into supply and demand-side resources. Solutions to the problems faced in managing transmission networks can be solved through flexibility obtained from consumers and prosumers varying their demand or through traditional generators, wind power generators and virtual power plants able to react to signals from the TSO [18]. In relation to the LEM, in the same way as the DSO, the TSO should formulate its needs as services requests according to the market standard, something that already happens in some current markets [32].

To properly exploit the available flexibility, some flexibility services that the aggregator can offer to the TSO have been identified in Table 5 [3,32]:

Table 5 – Flexibility services for TSO [3,32]

Service	Description
Primary, Secondary and Tertiary Control	Prosumers owns equipment which is able to support the grid frequency maintaining system stability and reliability.
Voltage Control	Reactive power control by large generators, capacitors and inverters on large wind farms
Grid Capacity Management	Use load flexibility aiming the optimization of the operational performance extending the components lifetime and reducing grid losses.
Controlled Islanding	Avoid supply interruption in a given grid section.

3.2.5. BALANCE RESPONSIBLE PARTIES (BRPS)

Imbalance settlement determines that every market agent must be aware of its own energy balance. In practice, these agents cannot maintain this balance by themselves, requiring an agent to assist them in this power balance [34]. In other words, the Imbalance Settlement is a process that settles discrepancies comparing the amount of contracted and actually generated or consumed electricity. When these values are different from the contracted amount of electricity the agents are exposed to the imbalance price. This mechanism works as an economic incentive because imbalance agents must pay this cost. [35] In order to solve this problem, the BRP role is defined as the responsible for the balance of production and consumption of its customers through technical resources or exchanges with other BRPs [36].

In the operation of BRPs, the use of flexibility services fits as an additional tool since they have great potential in maintaining the system balance. To take advantage of this flexibility, BRPs may have contracts with suppliers and aggregators. The interaction with aggregators in new LEM models is of fundamental importance in the acquisition of flexibility-based services and in the sale of balance services. Depending on the market model implemented, aggregators should have contracts with one or more BRPs in order to guarantee their energy balance. In addition to aggregators, DSOs and TSOs can benefit from the balance services provided by this agent [32].

To balance its portfolio, flexibility sources can be used for managing possible imbalances due to forecasting errors and minimize BRP electricity costs.[31]. USEF, a smart energy framework, listed some potential flexibility services for the BRP [3], presented in Table 6:

Table 6 – Flexibility services for BRP [3]

Service	Description
Intraday Portfolio Optimization	Shift loads from a high-price time interval to a low-price time interval in the intraday market and reduce its overall electricity costs.
Self-Balancing or Balance Service	Reduce imbalance with its portfolio and avoid imbalance charges.
Generation Optimization	Optimize the generation planning of central production units.
Day-Ahead Portfolio Optimization	Shift loads from a high-price time interval to a low-price time interval before the day-ahead market and reduce its overall electricity costs.

3.2.6. Suppliers and Producers

The role of the supplier in electric power systems is to provide energy to end-users according to their demand, while producers feed energy into the grid and help the security of the energy supply. In the future, the relationship between these agents and consumers should change. With the advent of distributed generation and the entry of prosumers, it might be a differentiation between new products and services that alter the interactions between agents. In this way, suppliers with better forecasting models will have a competitive advantage, because they will be able to optimize their generation assets and benefit from the sale of products aimed at solving market issues [3]. In the USEF framework [3], the role of the supplier is well-defined stating that, suppliers must provide energy to its customers. These agents agree on commercial terms for the supply and procurement of energy, forecast consumer load profile and source the energy through a BRP with which they have balance response agreements.

3.2.7. Energy Service Companies (ESCOs)

The European Commission [40] defines ESCOs as companies that guarantee energy savings and energy supply at a lower cost by offering services such as energy efficiency and renewable energy projects. ESCOs are a growing business in the European market as they can achieve a significant reduction in customer demand while their revenues are directly linked to the energy savings achieved by their customers [29]. As providers of energy-related services to the end user they need remote access and operation of equipment, including DR devices, in addition to information for better realization of off-site energy management. This form of insight services, energy optimization service and remote maintenance of ADS asset can be services present in the catalog of this stakeholder. This function can be purchased by the aggregator depending on the established market model [3].

3.3. Final Remarks

In this chapter, the LEM concept was detailed in order to present its concept and contextualize the main benefits and barriers to be faced when implementing this model. Next, several prerequisites that must be analyzed in order for the LEM to be functional were discussed and highlighted. Finally, the various players involved in the market were presented in order to show the services they can offer, their role in the market, and the interactions between them in the context of the LEM.

4. EVOLUTIONARY ALGORITHMS FOR ENERGY APPLICATIONS

Evolutionary computation is a sub-field of computational intelligence that include different algorithms for global optimization inspired by evolutionary processes [41]. Typically, the so-called evolutionary algorithms (EA) are population-based meta-heuristics that evolves an initial set of candidate solutions (i.e., a population or swarm) over iterations. The improvement of solutions in the evolutionary process is measured by a given fitness function. Thus, in each iteration, new solutions are generated using particular operators and those new solutions are introduced into the population depending on their fitness value (i.e., replacing solutions with lower performance). By doing this, it is expected that the population gradually evolves towards a promising area of the search space following the principles of natural/artificial selection [41].

4.1. DIFFERENTIAL EVOLUTION

Differential Evolution Algorithms (DE) are part of a wide range of EAs whose study has been growing and developing continuously [41]. EAs are inspired by biological processes with a terminology originated from the theory of natural evolution and genetics, where from an initial population the best adapted ones are recombined and mutated over the generations. As described in more detail in [42] DE uses a population of individuals where G is correlated with the generation number and the number of individuals per generation corresponds to $i = [1 \ldots N_p]$. The most common method used in the creation of the population is a random initialization of the solutions, considering the particular problem restrictions and characteristics. To create the new population of individuals, the recombination and mutation operators, that will be explained in the following subsections, are used. After this process, the individuals with the best fitness are selected and the rest are discarded in order to obtain better solutions in later generations.

The recombination and mutation operators contain two parameters (*F* and *Cr*) that are fundamental to the algorithm. In addition to these two parameters, the *NP* parameter also has a great value, with only these three being the parameters of the algorithm. *F* is the mutation constant and is related to the control of the mutation force. *Cr* is the recombination constant and is linked to diversity in the mutation process, and *NP* defines the population size.

In the evolutionary computing process, there are four important segments, sequentially, i) the strategy used to create the mutation of individuals, ii) the recombination, iii) verification of the viability of solutions iv) and the selection of individuals with the best fitness. In the first step, all $\overrightarrow{x_{\iota,G}} \in$ Pop individuals are evaluated each generation, the individual being evaluated is called the target vector $\overrightarrow{x_{\iota,G}}$. Using the mutation operator, a mutant individual $\overrightarrow{m_{\iota,G}}$ is designed for each target vector. The mutation operator varies in different applications called strategies, in this case study tests were performed using two different strategies DE/rand/1 and DE/target-to-best/1 which will be explained briefly in this section. The other 3 segments of the DE algorithm will be explained in the following subsections. The reader can obtain a complete explanation about the processes and state of the art of DE in [42].

Mutation Operator Strategies

The DE/rand/1 strategy operator is shown in equation (1), this is the standard DE mutation operator model where three random individuals of the current population, different from each other and from the target vector, make a linear combination in order to generate $\overrightarrow{\mathrm{m}_{\iota,\mathrm{G}}}$. Unlike the previous strategy, the DE/target-to-best/1 strategy acts changing the convergence capabilities of the algorithm using information related to the best individual found so far. The DE/target-to-best/1 strategy mutation operator is described as equation (2).

$$\overrightarrow{\mathrm{m}_{\iota,\mathrm{G}}} = \overrightarrow{x_{r1,G}} + \mathrm{F}(\overrightarrow{x_{r2,G}} - \overrightarrow{x_{r3,G}}) \tag{1}$$

$$\overrightarrow{\mathrm{m}_{\iota,\mathrm{G}}} = \overrightarrow{x_{\iota,G}} + \mathrm{F}(\overrightarrow{x_{best,G}} - \overrightarrow{x_{\iota,G}}) + \mathrm{F}(\overrightarrow{x_{r1,G}} - \overrightarrow{x_{r2,G}}) \tag{2}$$

Recombination Operator

The recombination operator is applied to create the trial vector $\overrightarrow{\mathrm{t}_{\mathrm{J},\iota,\mathrm{G}}}$ which corresponds to the combination between the target vector $\overrightarrow{x_{\iota,G}}$ and the individual mutant $\overrightarrow{m_{\iota,G}}$ according to equation (3). In this step *Cr* corresponds to the probability of choosing each of element of $\overrightarrow{m_{\iota,G}}$. *Rnd* is an integer between [*1*,*D*] that guarantees that at least one of the individuals in $\overrightarrow{m_{\iota,G}}$ will be selected to compose the new population.

$$\overrightarrow{\mathrm{t}_{\mathrm{J},\iota,\mathrm{G}}} = \begin{cases} \overrightarrow{\mathrm{m}_{\mathrm{J},\iota,\mathrm{G}}} & if\ \ (rand_{i,j}|0{,}1| < \mathrm{Cr})\ v\ (j = Rnd) \\ \overrightarrow{\mathrm{x}_{\mathrm{J},\iota,\mathrm{G}}} & otherwise \end{cases} \tag{3}$$

Boundary Verification

Mutation and recombination processes can generate solutions that do not respect the problem's constraints and are therefore not viable. Thus, the boundary verification occurs according to (4).

$$\overrightarrow{\mathrm{t}_{\mathrm{J},\iota,\mathrm{G}}} = \begin{cases} \overrightarrow{\mathrm{x}_{\mathrm{J},\mathrm{lb}}} & \text{if } \overrightarrow{\mathrm{t}_{\mathrm{J},\iota,\mathrm{G}}} < \overrightarrow{\mathrm{x}_{\mathrm{J},\mathrm{lb}}} \\ \overrightarrow{\mathrm{x}_{\mathrm{J},\mathrm{ub}}} & \text{if } \overrightarrow{\mathrm{t}_{\mathrm{J},\iota,\mathrm{G}}} > \overrightarrow{\mathrm{x}_{\mathrm{J},\mathrm{ub}}} \end{cases} \tag{4}$$

Selection

The selection occurs by comparing the fitness values of the objective function between the trial vector $\overrightarrow{t_{J,\iota,G}}$ and the target vector $\overrightarrow{x_{\iota,G}}$ in which the best individual is selected to compose the population of the next generation $Pop_{i,G+1}$ This selection is described by equation (5).

$$Pop_{i,G+1} = \begin{cases} \overrightarrow{t_{i,G}} \text{ if } f(\overrightarrow{t_{i,G}}) \leq f(\overrightarrow{x_{i,G}}) \\ \overrightarrow{x_{i,G}} \quad \text{otherwise} \end{cases} \tag{5}$$

4.1.1. HyDE (Hybrid Adaptive Differential Evolution)

Hybrid-adaptive DE (HyDE) is a self-adaptive EA proposed in [43] and inspired in the DE. HyDE incorporates different ideas from other EAs, such as an operator called "DE/target-to-perturbed_{best}/1" (which is a modification of the DE/target-to-best/1 strategy [42] with a perturbation of the best individual inspired by the evolutionary PSO [44], and the parameters self-adaptive mechanism of DE [45]. HyDE main operator is defined as:

$$\overrightarrow{\mathrm{m}_{\mathrm{i,G}}} = \overrightarrow{x_{i,G}} + F_i^1(\epsilon\ \overrightarrow{x_{best,G}} - \overrightarrow{x_{i,G}}) + F_i^2\ (\overrightarrow{x_{r1,G}} - \overrightarrow{x_{r2,G}}) \tag{6}$$

where F_i^1 and F_i^2, are scale factors in the range [0,1] independent for each individual i, and $\epsilon = \mathcal{N}(F_i^3, 1)$ is a perturbation factor equivalent to a random number taken from a normal distribution with mean F_i^3 and standard deviation 1. F_i^1, F_i^2 and F_i^3 are updated at each iteration following the same rule of DE algorithm (see Sect. III.B of [43]).

4.1.2. HyDE-DF (Hybrid Adaptive DE with Decay Function)

HyDE with decay function (HyDE-DF) is an improved version of HyDE used for function optimization [46]. It incorporates a decay function to perform a transition in the iteration process from the main operator of HyDE (11) to the basic operator of DE Eq. (7):

$$\overrightarrow{\mathrm{m}_{\mathrm{i,G}}} = \overrightarrow{x_{i,G}} + \delta_G * [F_i^1(\epsilon\ \overrightarrow{x_{best,G}} - \overrightarrow{x_{i,G}})] + F_i^2\ (\overrightarrow{x_{r1,G}} - \overrightarrow{x_{r2,G}}) \tag{7}$$

where δ_G factor is used to gradually decrease the influence of the term F_i^1 (ε $\overrightarrow{x_{best}} - \overrightarrow{x_{i,G}}$}) responsible for the fast convergence towards the best individual in the population. Therefore, δ_G is a function that decreases its value from 1 → 0 at each iteration mitigating the influence towards $\overrightarrow{x_{best}}$, and taking advantage of the inherent DE exploitation capabilities in later stages of the evolutionary process:

$$\delta_G = e^{1-1/a^2} \quad with \quad a = (GEN - G)/GEN \tag{8}$$

where a is a value that linearly decreases from 1 → 0. Such a decrease value of a is proportional to the number of generations GEN. The transition implemented in Hyde-DF allows an enhance phase of exploration in the early stage of evolution and stress the exploitation in later stages of the optimization. To remark that HyDE-DF achieved third place (out of 36 algorithms) in the 100-digit challenge in CEC/GECCO 2019 [46].

4.2. VORTEX SEARCH (VS)

Vortex search (VS) is classified as a single solution-based metaheuristic with a similar framework compared with other EAs [47]. Therefore, VS generates N_{vs} neighbor solutions at each iteration using a multivariate Gaussian distribution around the initial single solution. After that, those N_{vs} solutions are evaluated in the fitness function and the single solution is updated with the best solution found. The iterative process is repeated until a stop criterion set by the user is met [47]. The advantage of applying VS algorithm lays in its simplicity and effectiveness, and the fact that no associate parameters (apart from the number of neighbor solutions N_{vs} and iterations) need to be set or tuned.

5. LOCAL MARKET APPLICATION STUDY

5.1. MARKET MODEL DESCRIPTION

In the market model proposed by Kok et al. [48] the DSO procures flexibility while DR aggregators offer this type of product. Considering a competitive market context, the best combination of bids and offers must be found so the equilibrium price is reached and the participants adequate their products in order to decrease the costs and maximize profits. The services are settled through fixed term contracts which expose the obligations of both parts. The aggregators must provide fixed quantities of flexibility every day besides the reserve flexibility that eventually can be requested by the DSO through an external signal. The DSO is responsible for the stable and reliable energy supply, and its duty is utilizing the flexibility available to help with it. An exemplification model is shown in Figure 5.

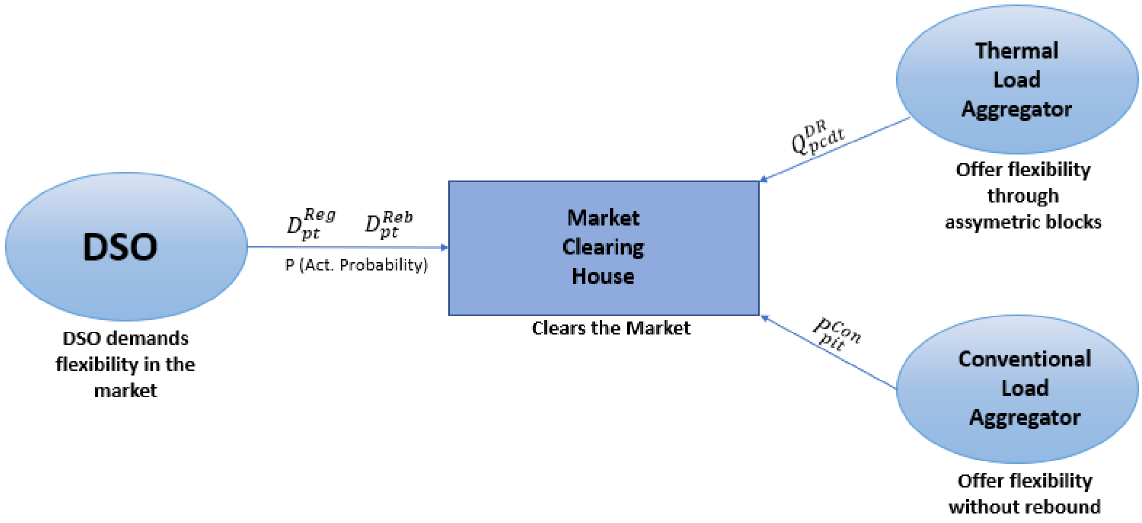


Figure 5 - Market Model Representation

Scheduled and Conditional are the two types of services concerted by the DSO and aggregators, in these two services the aggregators offer their flexibility products before Market Clearing. The information that must be provided by the DSO before the Market Clearing is the period in which it demands flexibility as well as the probability of activating the conditional service. Taking this into consideration, in [48] it was defined that, before the Market Clearing, for each type of service $p \in P$, every period in which each unit must provide flexibility the maximum quantity must be declared.

The aggregators function is making the accumulation of flexibility obtained in their portfolio into flexibility products that can be of interest to agents in the energy market. This accumulation comes from its customers who have the most diverse profiles. One of these is related to thermostatically controlled loads whose operation is different from the other types of loads because the temperature of a certain space must be maintained within a pre-established level. Thus, two types of agents are part of the market, the thermo load aggregators $c \in C$ and the conventional aggregators $i \in I$. Conventional aggregators are able to offer for each p and time step t service a maximum amount of load reduction P_{pit}, this flexibility that can be contracted and partially used by DSO. The thermal load aggregators, due to their rebound characteristics, offer their products in the form of asymmetric blocks, which must be completely used (not partially); thus ensuring that the load reduction is followed by an increase and vice versa. Each block is identified by $d \in D$ and its response at each time t is identified by the parameter Q_{pcdt}^{DR}.

The optimization function of this study is related to minimizing the market overall costs through the best combination of bids and offers for DR and is described by equation (9).

$$\text{minimize} \sum_{p \in P}^{R} \mathrm{R}C_p + \sum_{p \in P} P_p \, DC_p \tag{9}$$

This optimization is referred to a mixed integer linear problem defined through many functions and restrictions. Regarding the objective function, the dummy variables RC and DC are the reserve costs (or capacity costs) and the dispatch costs, respectively. The reserve costs defined in (10) refer to fixed costs and are not dependent on the number of times the service is activated. It represents the market costs associated with the DSO and aggregator operation. Regarding aggregators, the main cost is associated with the choice to reserve flexibility for the DSO-level instead of participating in another markets (e.g., at the TSO-level). For the DSO, the benefits of its market share are counted as a decrease in the overall cost of the system.

$$RC_p = \sum_{i \in \mathrm{I}} \sum_{t \in \mathrm{T}} C_{pit}^{R,Con} \, p_{pit} + \sum_{i \in \mathrm{I}} \sum_{t \in \mathrm{T}} C_{pcd}^{R,DR} \, r_{pcd} + \sum_{t \in \mathrm{T}} C_{pt}^{R,Reb} \, s_{pt} - C_p^{R,DSO} z_p \quad \forall \, \mathrm{p} \in \mathrm{P} \tag{10}$$

The first term of the Eq. (10) refers to the cost associated with conventional aggregators, where $C_{pit}^{R,Con}$ is equal to the reserve component cost (€/ kW) for unit *i* to meet service *p* at time *t*, and the upward regulation (load reduction) is given by p_{pit}. DR cost in the second term is related to the total cost of the asymmetric blocks offered by each aggregator *c*, where $C_{pcd}^{R,DR}$ is the cost of the block *d* and r_{pcd} is the number of blocks offered. The third term of the Eq. (2) corresponds to the rebound cost, this being the cost to DSO for the allowed rebound of the aggregators $c \in C$, $C_{pt}^{R,Reb}$ is the cost per kW of rebound, and s_{pt} is the amount of total rebound at each time *t*. The last term refers to the benefit to the DSO of activating the service (this term is negative because it decreases the total cost of the system). $C_p^{R,DSO}$ refers to the benefit of DSO while z_p is a binary variable that indicates which of the services has been selected.

The dispatch cost refers to the second term of Eq. (9) and is defined as (11):

$$DC_p = \sum_{i\in \mathrm{I}} \sum_{t\in \mathrm{T}} C_{pit}^{D,Con} p_{pit} + \sum_{i\in \mathrm{I}} \sum_{t\in \mathrm{T}} C_{pcd}^{D,DR} r_{pcd} + \sum_{t\in \mathrm{T}} C_{pt}^{D,Reb} s_{pt} - C_p^{D,DSO} z_p \quad \forall \mathrm{p} \in \mathrm{P} \tag{11}$$

where the terms are similar to those of equation (10) considering different parameter values associated with the costs. The load reduction is dependent on a DSO activation signal and is not mandatory for all days and periods. Thus, associated with the DC is the term P_p which indicates the daily probability of activation of the service p. This probability of activation is previously established by the DSO before the Market Clearing. Constraint (12) defines the amount of power that each aggregator *i* can offer for up regulation in each time *t* and service *p*, this being defined as the upper limit P_{pit}^{Con}

$$p_{pit} \le P_{pit}^{Con} \quad \forall p \in P, i \in I, t \in T \tag{12}$$

Aggregators *c* might offer many asymmetric blocks with different structures knowing that at least one of them must be activated. So, a variable called m_{pcd} is defined to indicate which block *d* offered for service *p* and aggregator *c* is selected. Equation (13) guarantees that at least one block is selected.

$$\sum_{d\in D} m_{pcd} \le z_p \quad \forall p \in P, c \in C \tag{13}$$

Equation (14) guarantees that only one of the services will be cleared by the market.

$$r_{pcd} \le B_{pcd}^{DR} m_{pcd} \quad \forall p \in P, c \in C, d \in D \tag{14}$$

The amount of total rebound possible is not unlimited as it could cause problems for the DSO. In this way, a limit of s_{pt} rebound to a maximum D_{pt}^{Reb} is defined by the DSO. Equation (15) guarantees this restriction.

$$s_{pt} \le D_{pt}^{Reb} z_p \quad \forall p \in P, t \in T \tag{15}$$

Constraint (16) defines a minimum amount of response required by the DSO for each period. That is, in each period the combination of bids from conventional units and the asymmetric blocks must match or exceed the requirement of the DSO (D_{pt}^{Reg}) considering the rebound effect at each time step:

$$\sum_{i \in I} p_{pit} + \sum_{c \in C} \sum_{d \in D} Q_{pcdt}^{DR} r_{pcd} \geq D_{pt}^{Reg} z_p - s_{pt} \quad \forall p \in P, t \in T \tag{16}$$

Finally, variables are bounded according to Equations. (17a) - (17d):

$$P_{pit} \geq 0 \quad \forall p \in P, i \in I, t \in T \tag{17a}$$

$$r_{pcd} \in Z_+ \quad \forall p \in P, c \in C, d \in D \tag{17b}$$

$$m_{pcd} \in \{0,1\} \quad \forall p \in P, c \in C, d \in D \tag{17c}$$

$$z_p \in \{0,1\} \quad \forall p \in P \tag{17d}$$

The following are some considerations regarding the case studies, which are divided into four experiments that can be summarized as:

- **Experiment 1**: Simulation of LEM model with 4 aggregators using DE/rand/1, DE/target-to-best/1, HyDE, HyDE-DF and VS algorithms;
- **Experiment 2**: Simulation of LEM model with 6 aggregators using DE/rand/1, DE/target-to-best/1, HyDE, HyDE-DF and VS algorithms;
- **Experiment 3**: Simulation of LEM model with 6 aggregators, with the addition of a distribution network mockup model, using DE/target-to-best/1, HyDE-DF and VS algorithms. The fitness function is modified to consider network constraints in this experiment;
- **Experiment 4**: Sensibility test of parameters *BBen*, D_{pt}^{Reg}, D_{pt}^{Reb} and P_{Con}^{Up} from experiment 3, using DE/target-to-best/1 and HyDE-DF algorithms.

Table 7 presents the list of experiments compactly.

Table 7 – List of Experiments

Experiment	Name	Number of Aggregators	Algorithms Utilised	Grid Utilised
1	DSO-Aggregator Contract Market	4	DE/rand/1 DE/target-to-best HyDE HyDE-DF Vortex Search	NO
2	Local Market Scalability Test	6	DE/rand/1 DE/target-to-best HyDE HyDE-DF Vortex Search	NO
3	DSO Network Validation in Flexibility Market	6	DE/target-to-best HyDE-DF Vortex Search	YES
4	Parameters Sensibility Analysis	6	DE/target-to-best HyDE-DF	YES

5.2. Experiment 1: DSO-Aggregator Contract Market

In this case study, the tests were divided into two parts. In the first part, the impact of the DE parameters using the DE/rand/1 and DE/target-to-best/1 algorithms was analyzed to know the best combination of these for carrying out the tests. In the second part, tests were made and the results obtained from the optimization problem were collected. After that, other algorithms such as VS, HyDE and HyDE-DF were used to offer a comparison of performance.

5.2.1. CASE STUDY DESCRIPTION

For this study, a market with 5 participants, the DSO and 4 aggregators, was considered. Among these aggregators, two of them are of conventional loads (*i1* and *i2*) and the other two of thermostatically controlled loads (*c1* and c2), *i1* and *i2* offer flexibility without rebound effect while *c1* and *c2* offer flexibility in the form of asymmetric blocks. DSO controls the market with monthly contracts. In this case study, the DSO demands flexibility in the periods between 17:00 and 18:00 hours as it aims to reduce the peak consumption in this time of the day. In this market, it was defined that the period of one hour before and one hour after the period that the DSO requires flexibility is allowed for rebound, i.e., thermostatically load aggregators must increase/decrease their consumption inside these periods. In order to execute this study, three DR services were considered, one of which is Scheduled (denoted by *Sched*) and the other two Conditional (referred as *Cond1* and *Cond2*), as described in the market model, Schedule services must be delivered every day while conditional services are dependent on a DSO activation signal.

The aggregators *c1* and *c2* offer blocks for each service *p*. The parameters used in the study are contained in the following tables. The cost associated with each block *d* offered is shown in Table 8. Table 9 gives the costs related to aggregators *i1* and i2 for each service p and the quantity of up regulation offered in the market. The benefit of the DSO clearing the market is given in Table 10. Table 11 is related to the costs of the rebound effect. Lastly, Table 12 exhibit the service requirement and the allowed rebound for each period.

Table 8 – Cost per Block and Number of Divisible Blocks

c	*d*	$C_{pcd}^{R,DR}$(€)	$C_{pcd}^{D,DR}$(€)	B_{pcd}^{DR}(€)
c1	*d1,d2*	150	55	2
c1	*d3,d4*	150	55	1
c2	*d1,d2,d3,d4*	150	60	1

Table 9 – Costs and Maximum Load Reduction (kW) for Each Conventional Aggregator

p	*i*	$C_{pit}^{R,Con}$(€)	$C_{pit}^{D,Con}$(€)	$P_{pit}^{Con}(kW)$
Sched	*i1*	2	4.0	50
Sched	*i2*	2	4.1	50
Cond1	*i1*	1	4.0	50
Cond1	*i2*	1	4.1	50

Cond2	*i1*	1	4.0	50
Cond2	*i2*	1	4.1	50

Table 10 – Reserve and Dispatch Benefit for the DSO

service(*p*)	$C_p^{R,DSO}$(€)	$C_p^{D,DSO}$(€)
Sched	400	2400
Cond1,Cond2	400	4000

Table 11 – Reserve and Dispatch Rebound Cost

service(*p*)	**Time period (t)**	$C_{pt}^{R,Reb}$(€)	$C_{pt}^{D,Reb}$(€)
Sched, Cond1,Cond2	16-16:59, 18-18:59	0	1

Table 12 – DSO Request and Rebound Allowed

service(*p*)	**Time period (t)**	$D_{pt}^{Reg}(kW)$	$D_{pt}^{Reb}(kW)$
Sched, Cond1,Cond2	17-17:59	100	0
Sched, Cond1,Cond2	16-16:59, 18-18:59	0	25

For each service, the aggregators *c1* and *c2* offer four asymmetric blocks (*d1* to *d4*). The respective response and rebound of these block offers are presented in Tables 13 and 14.

Table 13 – Aggregator *i1* block offers

Aggregator *i1* Blocks

Period(t)/Block(kW)	***d1***	***d2***	***d3***	***d4***
1	-20	0	-25	0
2	-20	0	-25	0
3	-20	0	-25	0
4	-20	0	-25	0
5	20	20	50	0
6	20	20	50	40
7	20	20	0	40
8	20	20	0	40
9	0	-20	0	-60
10	0	-20	0	-60
11	0	-20	0	0
12	0	-20	0	0

Table 14 - Aggregator *i2* block offers

Aggregator *i2* Blocks

Period(t)/Block(kW)	*d1*	*d2*	*d3*	*d4*
1	-30	0	0	0
2	-30	0	0	0
3	-30	0	-35	0
4	-30	0	-35	0
5	40	30	35	0
6	40	30	35	0
7	40	30	0	0
8	20	30	0	50
9	0	-40	0	-25
10	0	-40	0	-25
11	0	-40	0	0
12	0	0	0	0

5.2.2. ENCODING OF INDIVIDUALS

The encoding of individuals (solutions to the problem) plays a key role in the application of EAs. An individual is typically a vector containing the necessary variables for the evaluation of the objective function (9). In many optimization problems in energy systems several variables are used and the vector $\vec{x}$ can reach a high dimension. In the case of the analyzed DSO-Contract Market, some variables must be evaluated in order to obtain the lowest system overall cost. For instance, in this problem resolution the individual includes information about the selected service, the power values of conventional aggregators at each time *t* and service *p*, and the number of blocks used by thermal load aggregators, given a dimension of individuals equal to $1+t*N_i+N_c$. In this case study considering 2 conventional aggregators, 2 thermal load aggregators, 12 periods and 3 services the dimension of the solution vector is 27. The 1st value corresponds to the selected Z_p service (integer value), the following 24 values are positive numbers which represent the P_{pit} of each aggregator *i* for each time *t* and finally the last two values correspond to the block *d* selected by each aggregator *c*, these being integer values.

In order to limit possible solutions and more easily reach valid ones, the boundaries allowed for each individual of the solution population are established. These boundaries, called lower bounds and upper bounds, are related to the parameters established in the case study as well as real technical restrictions. Thus, in relation to the selected service, this variable is defined as an integer value in the range Z_p= [1, N_p]. The up-regulation values offered by conventional aggregators i are limited between lb = 0 and ub = P_{pit}^{con} while the chosen block d is represented by an integer and must be contained in the range of lb = 0 and ub = N_d. A random solution (18) is obtained as an initial population with values contained between the bounds defined as…

$$\overrightarrow{x_j} = \text{rand}\ (\overrightarrow{x_{lb}}\ ,\ \overrightarrow{x_{ub}}) \tag{18}$$

Since the problem has restrictions that are hardly perceived and solved by the algorithm, severe penalties are applied in case one of these is violated. In this way, the algorithm is helped to find feasible solutions and the best possible fitness value. In the proposed problem, these repair techniques refer to the fulfillment of the requirements proposed by the DSO regarding the amount of up regulation requested in critical periods and also the maximum amount of rebound allowed, adding the contribution of all aggregators c and i. In the up-regulation periods for each time t, the contributions of all aggregators are added together and subsequently a penalty per kWh different from that required by the DSO is applied, (this penalty is described by (19)). In rebound periods, the total amount of rebound in the period is shown by the s_{pt} variable. When this amount exceeds the allowed D_{pt}^{Reb} ,a penalty is applied per kWh exceeded, this penalty is described by (20). Finally, the fitness function of the problem becomes (21) by adding the repairs related to the unfeasibility of solutions.

$$\text{g1} = |\ (D_{pt}^{Reg}\ -\ P_{pit}\ )\ | \tag{19}$$

$$\text{g2} = \begin{cases} |D_{pt}^{Reg} - s_{pt}| & if\ \ s_{pt} > D_{pt}^{Reg} \\ 0 & if\ \ s_{pt} \leq D_{pt}^{Reg} \end{cases} \tag{20}$$

$$\text{F}\ (x') = \text{f}\ (x') + \sum_{j=1}^{J} g_i\ *\ R \tag{21}$$

Now that we defined the encoding of individuals and the fitness function, we can apply some EA to solve the problem. So was chosen two differential evolution (DE) variants, one single-based solution heuristic called vortex search (VS) algorithm [47], and two self-adaptive versions of DE called HyDE and HyDE-DF (selected due to its success in many applications and easy implementation [46].

5.2.3. PARAMETERS TUNING

Assessing the impact of each of the DE parameters is the purpose of this subsection, thus tests were carried out whose intention was to identify the best combination of the parameters *F*, *Cr, NP and G* for DE/rand/1 and DE/target-to-best/1. Three tests were performed, the first of which referring to the parameters *F* and *Cr*, the second *NP* parameter and the third to the number of generations (*G*). In the first experiment, the values of *F* and *Cr* were varied from 0.1 to 1 and tests were performed with all combinations. In these evaluations the number of population and generations were fixed with *NP* equal to 30 and *G* equal to 4000, in addition 10 races were held. Figures 6 and 7 show the HeatMaps for the fitness results found with each combination of parameters F and *Cr*. In these HeatMaps, the darkest points refer to better fitness values, that is, lower values of overall costs in equation (5). To obtain better visualization of the results, all values greater than 0were set to a white color. Figure 6 shows the HeatMap related to the DE/rand/1 strategy. It can be seen that lower *F* values lead to much worse fitness values than higher *F* values while lower *Cr* values have better fitness than higher *Cr* but with less variation. Figure 7 shows the HeatMap related to the DE/target-to-best/1 strategy and the evaluation of its results is similar to the previous strategy. Table 15 presents the best values of *F* and *Cr* found in the tuning of parameter and their respective average execution time and fitness as well as the standard deviation along the 10 runs.

Table 15 - Best DE tuning of *F* and *Cr* values

Method		Fitness	Time/Run (sec)
	(*F,Cr*)	**Ave. ± Std**	**Ave. ± Std**
DE/rand/1	(1.0 , 0.2)	-1080.2 ± 6.4	565,5 ± 41,4
DE/target-to-best/1	(1.0 , 0.1)	-1049 ± 100.1	562,3 ± 14,43

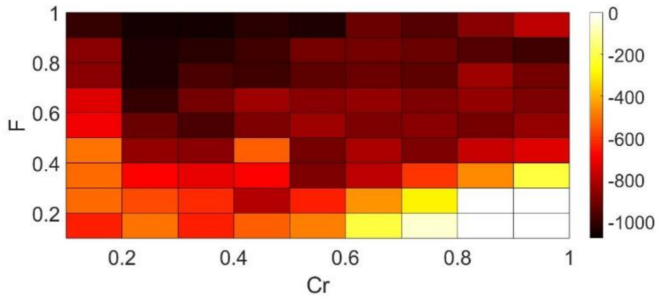


Figure 6 - HeatMap of strategy DE/rand/1

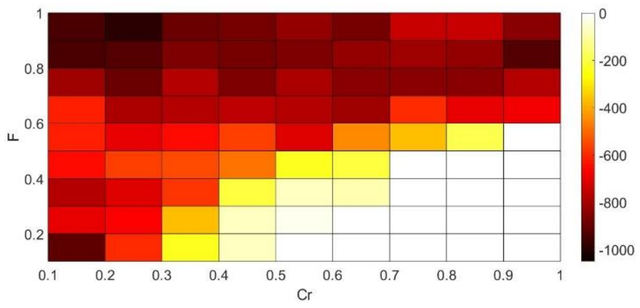


Figure 7 - HeatMap of strategy DE/target-to-best/1

Using the best values of *F* and *Cr* according to Table 14, the second test was accomplished in order to test the influence of the *NP* values when finding a better solution. Thus, the experiment was done, varying *NP* with a step size of 10 with values of 10 < *NP* <100 in order to compare the results. The value of the generations was varied according to the equation $Gen = \lceil 120000 / NP \rceil$ so that the objective function was evaluated the same number of times in all runs and the comparison was performed fairly. Figure 8 shows the variation in the fitness value referring to the assessment with each *NP* for each of the strategies using the optimal combination of *F* and *Cr* for DE/rand/1, the values obtained refer to the average of 10 runs performed. With these results it is possible to observe that for both cases the value of the objective function improves as the population increases up to *NP* = 70, after this point the *NP* increase interferes negatively in obtaining a better fitness. Figure 9 shows the variation in the fitness value using the optimal combination of *F* and *Cr* for DE/target-to-best/1, where it is possible to observe the same behavior of the other test, with *NP* = 70 being value of the best performance.

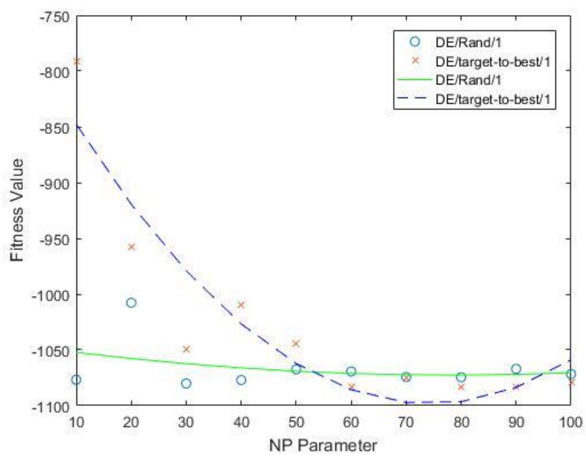


Figure 8 - Fitness in function of *NP* parameter variation with *F*=1and *Cr*=0.2

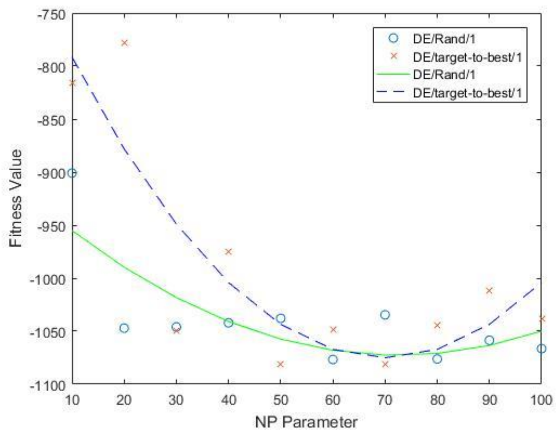


Figure 9 - Fitness in function of *NP* parameter variation with *F*=1and *Cr*=0.1

After the exploration of the *NP* parameter, the analysis of the relationship between the number of generations and the result obtained was started. Using the optimum values of *F* and *Cr* according to table x and *NP* fixed at 70, the number of generations was varied in a step size of 500 in the range [500 5000]. The results of these experiments are shown in figures 6 and 7. The results of the experiments demonstrate that for both cases the results are better when increasing the variation until 3500 generations, however from *G* equal to 3500 until *G* equal to 5000 the fitness comes back to get worse every generation.

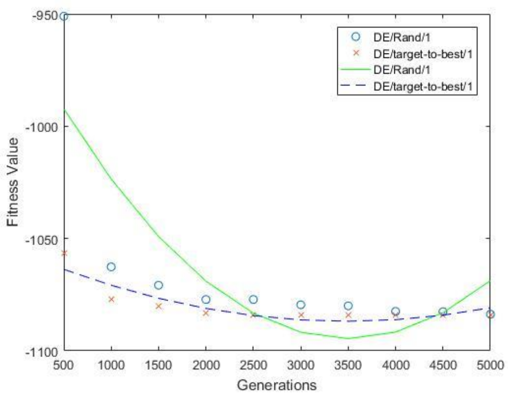


Figure 10 - Fitness in function of *G* parameter variation with *F*=1and *Cr*=0.2

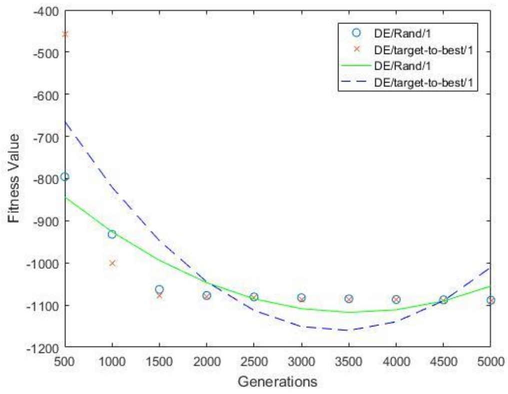


Figure 11 - Fitness in function of *G* parameter variation with *F*=1and *Cr*=0.1

Finally, after tuning the parameters, their ideal values were established to carry out the final tests of the case study. Regarding the DE/rand/1 algorithm, the values found were *F* = 1.0, *Cr* = 0.1, *NP* = 70 and *G* = 3500, while for the DE/target-to-best/1 algorithm the only difference occurs in the parameter *Cr* this being equal to 0.2.

5.2.4. PERFORMANCE ANALYSIS

In this subsection the two algorithms (DE/rand/1 an DE/target-to-best/1), whose parameters have been specified, are compared with other available algorithms (HyDE, HyDE-DF and VS) in order to compare their performances. To perform the experiments, the best values of *F* and *Cr* found for the two DE algorithms were used, as well as 3500 generations of individuals for these and the other algorithms so that the objective function is evaluated the same number of times for all algorithms. Using these parameters, Figure 12 shows the convergence of both strategies over the generations. As expected throughout the iterations the result becomes more negative as this is a minimization function that aims to reduce the overall cost. In both cases the convergence rate is similar, both quickly slowing down when near 500 generations, and with DE/rand/1 a little bit faster than the rest of algorithms. All the algorithms converge to very close results. For instance DE/target-to-best/1 converges in generation 3500 to a fitness of -1087.38 while fitness in DE/rand/1 was -1080.9.

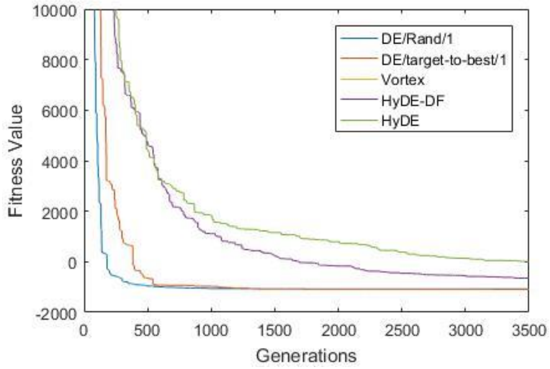


Figure 12 - Experiment 1 Algorithms Convergence

In addition to this analysis, tests were performed with other algorithms to compare results and computational time. The VS, HyDE and HyDE-DF algorithms were used with the parameters that, by experimentation, generally lead to acceptable solutions. Again, in order to have a fair comparison for the three methods, the same population number *NP* = 70 was used, so that the objective function is evaluated the same number of times. These tested algorithms converged to worse solutions when compared to the DE algorithms, being also slower in the convergence to these values. At the end of the generations, the fitness value for VS was -739.9, for HyDE-DF was -649.2 and for HyDE it was 9.9.

The results are shown in Table 16, in which the mean and standard deviation of the values obtained in 10 runs are presented for each algorithm.

Table 16- Experiment 1: Results for each method (€)

Method	Fitness	Reserve Cost	Dispatch Cost	Time/Run (s)
DE/rand/1	-1080,09 ± 3,29	148,85 ± 1,02	-2730,98 ± 5,59	9,00 ± 0,28
DE/target-to-best/1	-1087,38 ± 2,59	145,79 ± 0,77	-2740,39 ± 4,69	8,60 ± 0,15
Vortex	-739,93 ± 230,3	220,49 ± 85,0	-2431,13 ± 494,0	12,32 ± 1,0
HyDE-DF	-649,16 ± 153,7	178,27 ± 66,3	-2545,69 ± 481,8	11,64 ± 1,6
HyDE	9,92 ± 160,7	250,96 ± 131,6	-2081,14 ± 829,6	12,24 ± 1,5

Figure 13 was elaborated, which graphically demonstrates the best result obtained among all runs and algorithms. It is related to the DE/target-to-best/1 3rd run, which fitness is -1091,7 with RC = 145,3 and DC = -2749. In this run a conditional service, *Cond2*, was selected in the market clearing. The blocks selected of the thermostatically controlled loads aggregators were block 1 to aggregator *c1* and block 2 to aggregator *c2*. Finally, aggregator *i1* was cleared in both up regulation and rebound period and aggregator *i2* was activated in just one period of up regulation.

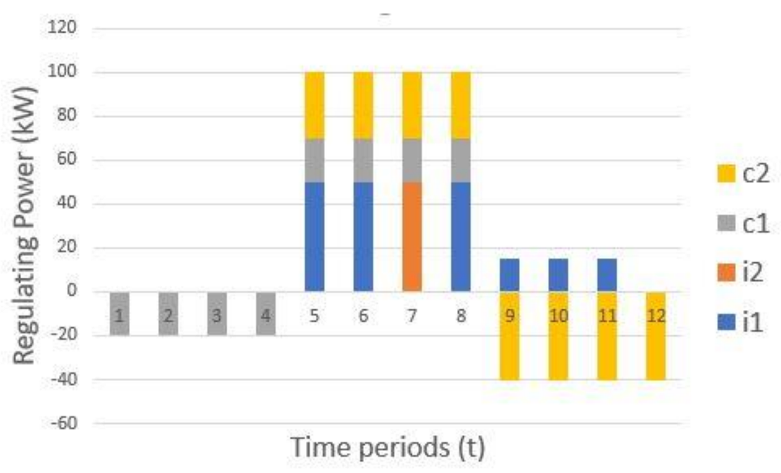


Figure 13 – Experiment 1: Upward and Downward Regulation

5.3. EXPERIMENT 2: LOCAL MARKET SCALABILITY TEST

5.3.1. STUDY DESCRIPTION

The purpose of Experiment 2 is to identify the difference in the Market Clearing results and test the scalability of the algorithms when adding aggregators and their offers to the market. In order to do this, the same market model presented in subsection 5.1 was used, that is, the Market Clearing presented in equations 9 to 17 remains the same. For this study, 7 participants are considered, namely the DSO and 6 aggregators. For the aggregators were kept the four presented in the previous study (two of conventional loads (*i1* and *i2*) and the other two of thermostatically controlled loads (*c1* and *c2*)). In addition, aggregators *i3* and *c3* were added to the problem, where *i3* is a conventional load aggregator and *c3* a thermostatically controlled load aggregator. The parameters referring to the aggregators *i1, i2, c1 and c2* as well as DSO request and allowed rebound remained the same as presented in the Tables 8 to 14. Regarding the aggregator *i3* the parameters presented in Table 17 were used. Table 18 presents aggregator *c3* parameters while Table 19 presents its block offers.

Table 17 – Conventional Aggregator *i3* Parameters

p	***i***	$C_{pit}^{R,Con}$ **(€)**	$C_{pit}^{D,Con}$ **(€)**	P_{pit}^{Con} **(kW)**
Sched	*i3*	1	3.6	50
Cond1	*i3*	1	3.6	50
Cond2	*i3*	1	3.6	50

Table 18 – Thermostatically Controlled Load Aggregator *c3* Parameters

c	***d***	$C_{pcd}^{R,DR}$ (€)	$C_{pcd}^{D,DR}$ (€)	B_{pcd}^{DR}
c1	*d1,d2,d3 and d4*	135	49.5	1

Table 19 - Thermostatically Controlled Load Aggregator *c3* Block Offers

Aggregator *c3* Blocks				
Period(t)/Block(kW)	***d1***	***d2***	***d3***	***d4***
1	-5	0	0	0
2	-5	0	0	0
3	-10	-10	-20	0
4	-10	-10	-20	0
5	10	10	15	0
6	10	10	15	10
7	10	10	10	10
8	0	10	0	10
9	0	-10	0	-10
10	0	-10	0	-10
11	0	0	0	-10
12	0	0	0	0

To perform the experiment, was utilized the two DE algorithms as well as HyDE, HyDE-DF and VS. The same values of *F* and *Cr* from experiment 1 were used for the two DE algorithms. To have a fair comparison and the objective function is evaluated the same number of times, NP = 70 and 3500 generations were performed for all algorithms.

5.3.2. RESULTS AND ANALYSIS

With the parameters described in subsection 5.3.1, tests were performed with each algorithm on 10 runs. Then Figure 14 is obtained, which shows the convergence of the algorithms over the generations. When compared all algorithms converge to similar results between 500 and 1000 iterations. The DE/target-to-best and VS algorithms converge faster than the others tested and, as in experiment 1, the differential evolution algorithms reached better solutions then the others. Final results at the end of generations showed fitness value of -1139,60 for DE/rand, -1100,82 for DE/target-to-best, -1078,81, for VS, -1083,60 for HyDE-DF and -1039,09 for HyDE.

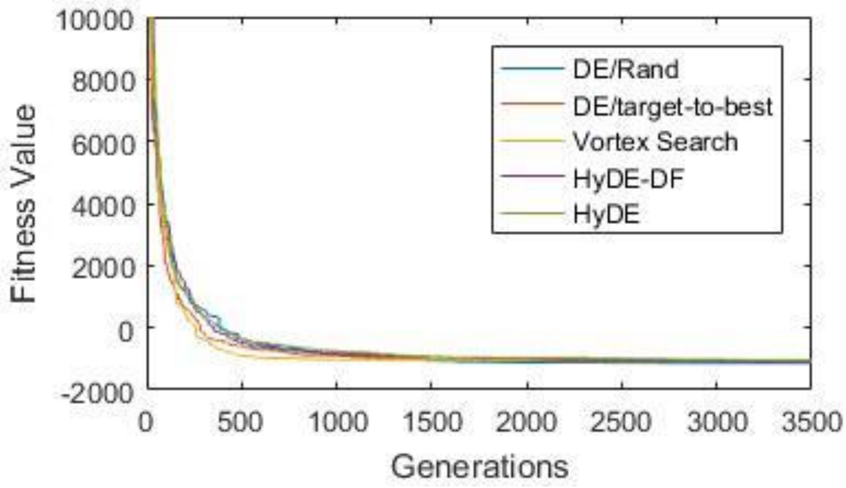


Figure 14 – Experiment 2 Algorithms Convergence

The results, in which the mean and standard deviation of the values obtained in 10 runs are presented for each algorithm, in Table 20.

Table 20 – Experiment 2: Results for each method (€)

Method	Fitness	Reserve Cost	Dispatch Cost	Time/Run (s)
DE/rand/1	-1139,60 ± 23,79	25,00 ± 23,84	-2588,00 ± 105,36	10,62 ± 0,13
DE/target-to-best/1	-1100,82 ± 38,66	24,99 ± 31,99	-2527,90 ± 88,45	11,24 ± 1,13
Vortex	-1078,81 ± 77,32	60,24 ± 100,65	-2531,23 ± 105,35	11,52 ± 0,48
HyDE-DF	-1083,60 ± 21,17	62,67 ± 20,59	-2678,16 ± 66,27	10,41 ± 0,66
HyDE	-1039,09 ± 40,02	75,77 ± 44,69	-2674,41 ± 96,62	11,25 ± 0,17

By comparing the results in Table 20 with those of the previous experiment in Table 16 it can be seen that with the addition of more competition in the market it can achieve better results in all algorithms. However, when comparing the execution time of each run one can notice the increase in time for all algorithms. To illustrate the results obtained, Figure 15 was elaborated, graphically demonstrating the best result obtained among all runs and algorithms. The figure is related to the results obtained with the 9th run of DE/target-to-best/1, in which a fitness of -1176,25 was achieved with RC = 50,0 and DC = -2725. As in experiment 1, a conditional service, *Cond2*, was selected in the market clearing. One block was selected of the thermostatically controlled loads aggregators, which is block 1 from aggregator *c1*. Finally, aggregator *i1* was cleared in periods 7 and 8 while aggregator *i3* was activated in all up-regulation periods.

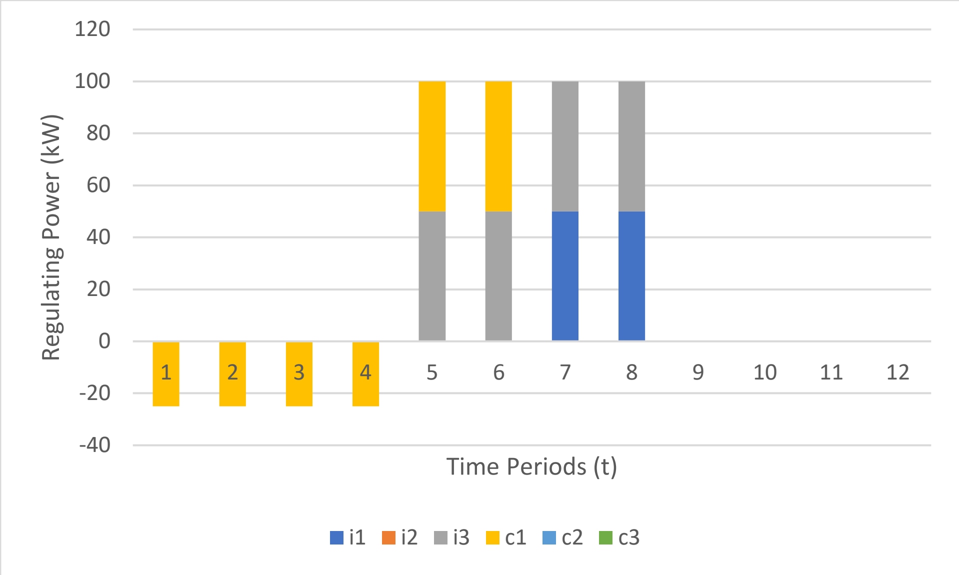


Figure 15 - Experiment 1: Upward and Downward Regulation

5.4. Experiment 3: DSO Network Validation in Flexibility Market

The application of local markets will require technology devices that supports and operates all market transactions in a fast, secure, and reliable way. To be efficient this mechanism must relate the technical and economic aspects of the market, so that the operation remains stable and managed in an optimal way. Thus, in order to expand the previous case studies, along the two new aggregators from experiment 2, an electrical network model was added to the problem, a distribution network model of the BISITE laboratory from University of Salamanca [49]. This network presents a 13-bus network with a 30MVA substation, 25 load points and high penetration of DER.

5.4.1. BISITE Laboratory Developed City Model

The city model developed by BISITE laboratory is intended to conduct studies on the high penetration of DER in the power grid and to formulate solutions for local energy markets [50]. In the model, a 13-bus distribution network with a 30MVA substation and several distributed generation units is considered. There are 15 DG units, 2 wind power plants and 13 PV parks that represent 27% (10925 MW) of the total installed power, 24% of which is wind generation and 3% PV generation. In the city six types of loads were differentiated, whose demand characteristics and flexibility service possibilities are different in some aspects among them. The types of loads presented are:

- **Residential Buildings:** This type of consumer may or may not have its own generation, micro or nano generation, through its photovoltaic panels. When they do, their own generation is deducted from their consumption when their demand is greater than the generation and made available to the grid in the other periods. This consumer is characterized in LEM as a prosumer, given its generation as well as its availability to participate in aggregation for flexibility services. Consumers without self-generation can also be aggregated and offer flexibility services such as energy curtailment and/or load shifting;

- **Office Buildings:** These are prosumers with different demand and generation characteristics than residential buildings. The high demand and energy generation generates different opportunities to offer flexibility services. An example is the services related to thermal loads with rebound that can be modeled and offered to the LEM;

- **Hospital and Fire Station:** Priority loads of the power grid that have diesel cogeneration so that their supply is not affected by adverse grid conditions. These consumers may provide flexibility in very specific and well-studied situations since their energy demand is paramount at all times to perform their activities;

- **Fast or Slow EV Charging:** Parking lots for charging electric vehicles. They have a high demand for electricity and in the future may offer energy to the grid through V2G as well as flexibility by encouraging the change of charging periods.

The data regarding agents' consumption contains one week of input data for every 15 minutes of the week between 03/19/2017 and 03/25/2017. The single line diagram, taken from [50], of the 13-bus, 30kV medium voltage distribution network is presented in Figure 16.

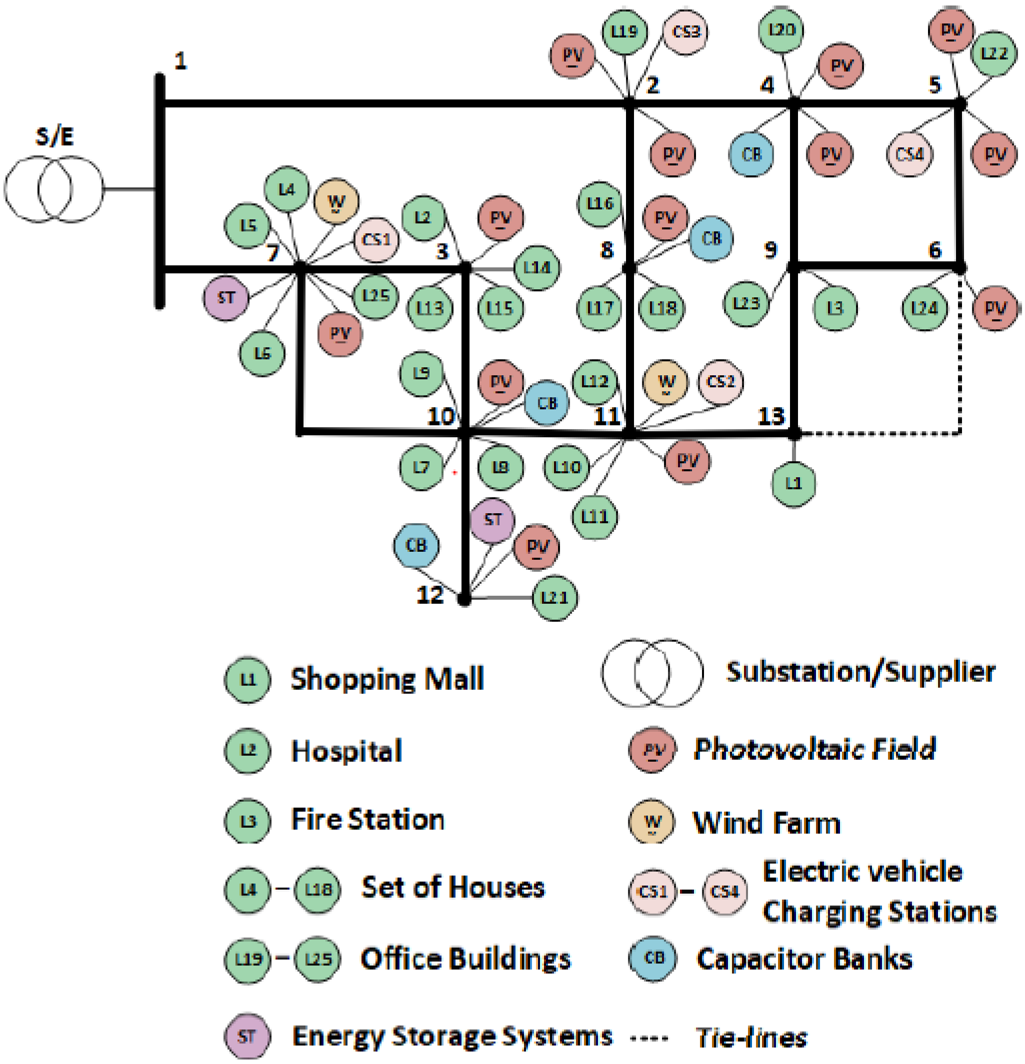


Figure 16 – Distribution Network Single-Line Diagram. Modified from [50]

When proceeding with the data treatment several graphs regarding the behavior of the market loads can be made for analysis. It is presented in Figure 17 the total market demand. It is noticed in this graphic a daily demand pattern similar to the "Duck Curve" [51] with a large increase in consumption between 5 p.m. and 7 p.m.

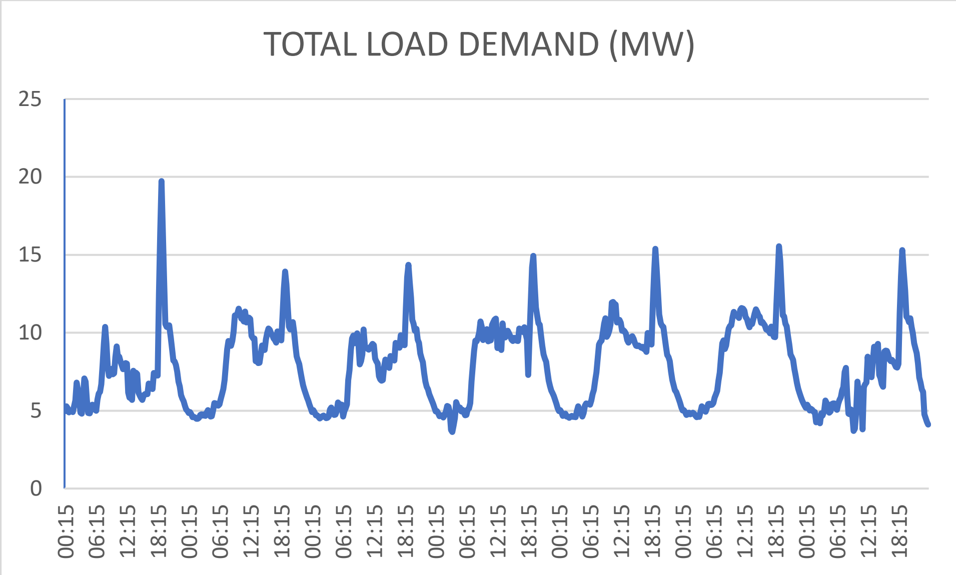


Figure 17 – Distribution Network Load Demand

Figure 18 presents the power demand per bus. One can notice in the graphic the similar behavior in the form of the "Duck Curve" in all buses, being the buses 13, 12, 9 and 7 those that present the greatest demand for energy respectively. It should be noted that the demand corresponds to the energy consumption subtracted from the local generation.

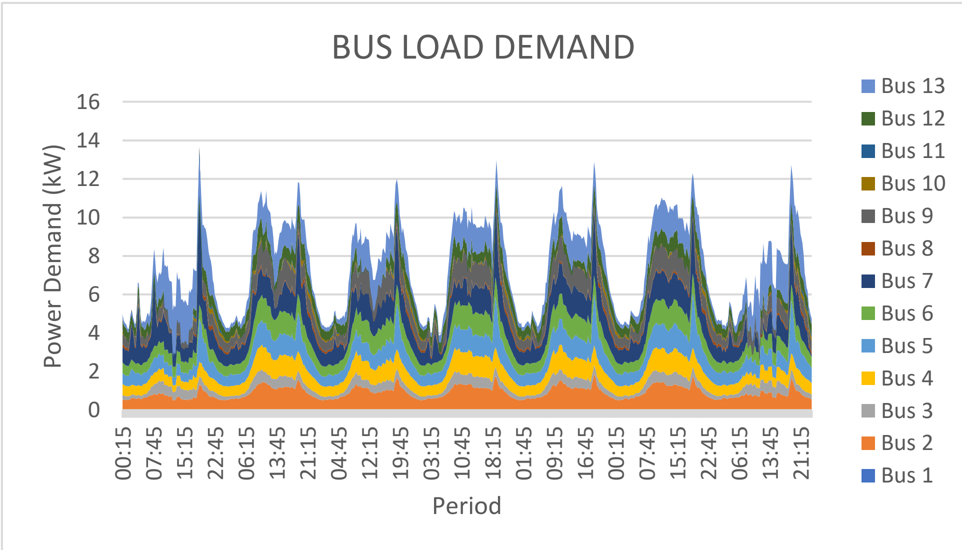


Figure 18 – Distribution Network Buses Load Demand

Bus 13, with the highest power demand, is characterized for containing exclusively the Commercial Mall. Bus 12 contains office buildings with PV generation totally used locally. Bus number 9 is differentiated by the presence of a fire station while bus 7 presents several types of loads with emphasis on parking lots of slow EV charging.

Figure 19 presents the LEM generation alone. It is noticed the large energy generation at bar 12 referring to the PV panels present in one of the office buildings as well as at bars 11 and 7 where the wind power plants are present.

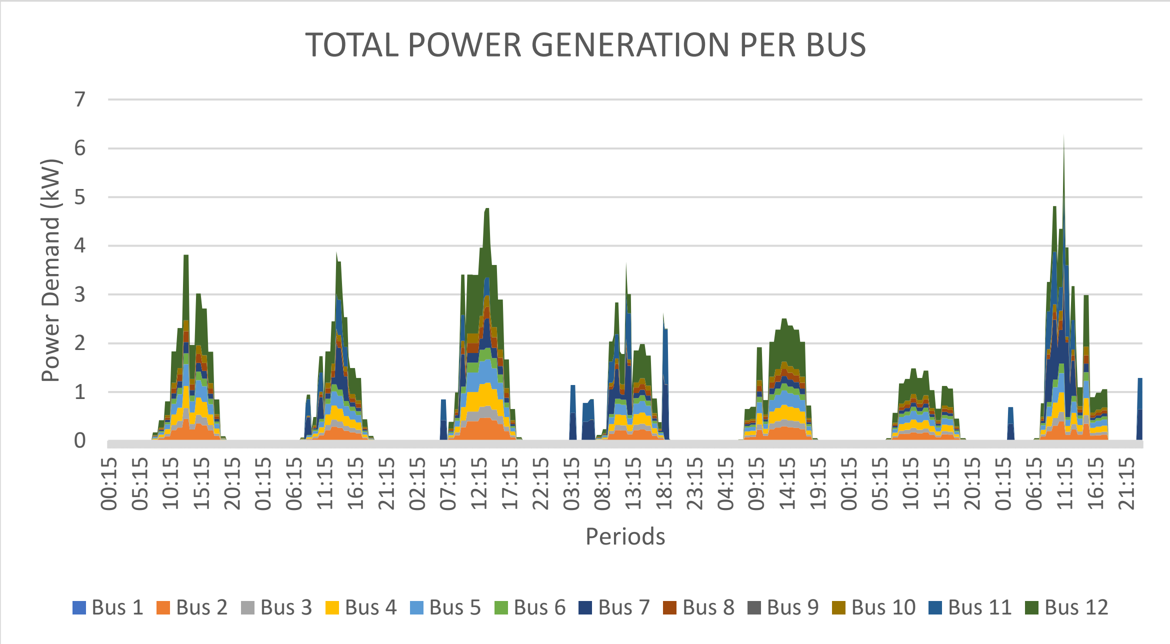


Figure 19 – Buses Generation

With this daily data, the DSO will be able to simulate the optimal power flow and identify areas where possible congestion or voltage problems may occur. So, It will be able to demand flexibility services from the market to help solve problems in an economical, feasible and beneficial way for both parties.

5.4.2. STUDY DESCRIPTION

The objective of this study is considering the addition of the network model from BISITE laboratory to the previous problem. To this end the loads that each aggregator controls in the model were defined, these loads may eventually offer consumption reduction services when requested. Table 21 shows the loads that each aggregator controls and in which buses they are located.

Table 21 – Aggregators Load and Location

Aggregator	Type of Load	Type of Service	Buses Located
i1	Residential Buildings	Conventional Load Reduction	7, 10 and 11
i2	Residential Buildings	Conventional Load Reduction	3 and 8
i3	Fast and Slow EV Charging Parks	Conventional Load Reduction	2, 5, 7 and 11
c1	Shopping Mall, Hospital and Fire Station	Load Reduction with Rebound	3, 9 and 13
c2	Office Buildings	Load Reduction with Rebound	2, 4, 5 and 12
c3	Office Buildings	Load Reduction with Rebound	6, 7 and 9

DSO controls the market with monthly contracts, in this case study the DSO demands flexibility in the periods with increased demand, when congestion, voltage and losses problems may arise. When analyzing Figure 17 referring to the total market demand, it is possible to notice an exponential increase in energy demand between 4p.m. and 7p.m. Thus, for this experiment it was defined, similarly to the previous experiment, that the DSO requires flexibility between 5p.m. and 6p.m. with one hour before and one hour after for the allowed rebound. To execute this study, the same three DR services were considered, one of which is Scheduled (denoted *Sched*) and the other two Conditional (referred to as *Cond1* and *Cond2*). The reduction requested in the market clearing for each aggregator are then divided among the buses it has control.

To be able to measure the results and the best offers to be selected in the Market Clearing the free file type.m package MATPOWER was used to run the power flow of the network [52]. With MATPOWER, a open source tool for electric power system simulations and optimization [52], by indicating the input data regarding the network, the standard algorithm solves the power flow by Newton's method with a complete Jacobian matrix at each iteration and finally provides us with the optimal power flow of the network. Thus, with the data regarding the network, the power flow before and after the use of flexibility can be obtained, one can consider the reduction of losses and the reduction of congestion in the lines as a crucial factor in the choice of services offered by the aggregators and add this generated value to the fitness function of the problem.

To identify the initial situation of the network, the power flow in the regulating periods were first simulated, without the reduction requested by the DSO. This way it is possible to obtain an overview of the network and use this information to choose the best flexibility services to reduce network congestion. To perform the simulation with MATPOWER, as previously described, one must provide information about the grid such as number of buses, interconnections between buses, bus types, power flow limit, impedance, reactance, and resistance values as well as demand and generation in each node, among others. Some of the physical grid parameters as well as simulation base values are presented in Table 22. To carry out the network simulation it was used the average of the demand and generation values, whose data refer to 7 days, in order to mitigate possible atypical values in case a random day was chosen. After simulating the initial case the results referring to the nodes and branches are made available by MATPOWER and are displayed between Tables 23 and 30.

Table 22 – Network Physical Parameters

From Bus	To Bus	r(p.u)	x(p.u)	c(p.u)	Power Flow Limit (p.u.)
1	2	0.000026	0.000020	0.000000	11.40
1	7	0.000051	0.000041	0.000000	11.40
2	4	0.000108	0.000038	0.000000	8.31
2	8	0.000086	0.000030	0.000000	8.31
3	7	0.000065	0.000023	0.000000	8.31
3	10	0.000086	0.000030	0.000000	8.31

4	5	0.000151	0.000053	0.000000	8.31
4	9	0.000065	0.000023	0.000000	8.31
5	6	0.000108	0.000038	0.000000	8.31
6	9	0.000043	0.000015	0.000000	8.31
7	10	0.000645	0.000225	0.000000	8.31
8	11	0.000108	0.000038	0.000000	8.31
9	13	0.000108	0.000038	0.000000	8.31
10	11	0.000043	0.000015	0.000000	8.31
10	12	0.000301	0.000105	0.000000	8.31
11	13	0.000032	0.000011	0.000000	8.31
Voltage (kV)		**Base Power (MVA)**		**Zbase (ohm)**	
30		1		900	

Table 23 – Initial Network Bus Data (5p.m-5:15 p.m Period)

```
================================================================================
|      Bus Data
================================================================================
 Bus      Voltage          Generation             Load
  #   Mag(pu) Ang(deg)   P (MW)   Q (MVAr)   P (MW)   Q (MVAr)
----- ------- --------  --------  --------  --------  --------
    1  1.000    0.000*     8.70      2.64       -         -
    2  1.000   -0.004      0.08      0.02      1.02      0.31
    3  1.000   -0.005      0.04      0.01      0.48      0.14
    4  0.999   -0.005      0.08      0.02      1.00      0.30
    5  0.999   -0.005      0.08      0.02      0.99      0.30
    6  0.999   -0.005      0.04      0.01      0.99      0.30
    7  1.000   -0.005      0.04      0.01      1.17      0.35
    8  1.000   -0.004      0.04      0.01      0.09      0.03
    9  0.999   -0.005       -         -        0.96      0.29
   10  1.000   -0.005      0.04      0.01      0.20      0.06
   11  1.000   -0.005      0.11      0.03      0.13      0.04
   12  0.999   -0.005      0.23      0.07      0.91      0.28
   13  0.999   -0.005       -         -        1.52      0.46
                        --------  --------  --------  --------
               Total:      9.46      2.87      9.45      2.86
```

Table 24 - – Initial Network Branch Data (5p.m - 5:15 p.m Period)

Branch Data								
Brnch	From	To	From Bus Injection		To Bus Injection		Loss (I^2 * Z)	
#	Bus	Bus	P (MW)	Q (MVAr)	P (MW)	Q (MVAr)	P (MW)	Q (MVAr)
1	1	2	5.52	1.64	-5.52	-1.64	0.001	0.00
2	1	7	3.18	1.00	-3.18	-1.00	0.001	0.00
3	2	4	3.10	0.93	-3.10	-0.93	0.001	0.00
4	2	8	1.48	0.42	-1.48	-0.42	0.000	0.00
5	3	7	-1.71	-0.55	1.71	0.55	0.000	0.00
6	3	10	1.27	0.41	-1.27	-0.41	0.000	0.00
7	4	5	0.87	0.26	-0.87	-0.26	0.000	0.00
8	4	9	1.30	0.38	-1.30	-0.38	0.000	0.00
9	5	6	-0.04	-0.01	0.04	0.01	0.000	0.00
10	6	9	-0.99	-0.30	0.99	0.30	0.000	0.00
11	7	10	0.34	0.11	-0.34	-0.11	0.000	0.00
12	8	11	1.42	0.41	-1.42	-0.41	0.000	0.00
13	9	13	-0.65	-0.21	0.65	0.21	0.000	0.00
14	10	11	0.77	0.27	-0.77	-0.27	0.000	0.00
15	10	12	0.68	0.21	-0.68	-0.21	0.000	0.00
16	11	13	2.16	0.67	-2.16	-0.67	0.000	0.00
						Total:	0.004	0.00

Table 25 - Initial Network Bus Data (5:15p.m -5:30p.m Period)

Bus Data						
Bus	Voltage		Generation		Load	
#	Mag(pu)	Ang(deg)	P (MW)	Q (MVAr)	P (MW)	Q (MVAr)
1	1.000	0.000*	8.41	2.55	-	-
2	1.000	-0.004	0.08	0.02	1.01	0.31
3	1.000	-0.005	0.04	0.01	0.48	0.14
4	0.999	-0.005	0.08	0.02	0.98	0.30
5	0.999	-0.005	0.08	0.02	0.97	0.29
6	0.999	-0.005	0.04	0.01	0.97	0.29
7	1.000	-0.004	0.20	0.06	1.21	0.37
8	1.000	-0.004	0.04	0.01	0.10	0.03
9	0.999	-0.005	-	-	0.94	0.28
10	1.000	-0.005	0.04	0.01	0.21	0.06
11	1.000	-0.005	0.17	0.05	0.13	0.04
12	0.999	-0.005	0.23	0.07	0.89	0.27
13	0.999	-0.005	-	-	1.50	0.45
		Total:	9.39	2.85	9.38	2.84

Table 26 - Initial Network Branch Data (5:15p.m -5:30p.m Period)

Branch Data								
Brnch	From	To	From Bus Injection		To Bus Injection		Loss (I^2 * Z)	
#	Bus	Bus	P (MW)	Q (MVAr)	P (MW)	Q (MVAr)	P (MW)	Q (MVAr)
1	1	2	5.38	1.60	-5.38	-1.60	0.001	0.00
2	1	7	3.03	0.95	-3.03	-0.95	0.001	0.00
3	2	4	3.02	0.91	-3.02	-0.90	0.001	0.00
4	2	8	1.43	0.41	-1.43	-0.41	0.000	0.00
5	3	7	-1.68	-0.53	1.68	0.53	0.000	0.00
6	3	10	1.24	0.40	-1.24	-0.40	0.000	0.00
7	4	5	0.85	0.26	-0.85	-0.26	0.000	0.00
8	4	9	1.26	0.37	-1.26	-0.37	0.000	0.00
9	5	6	-0.04	-0.02	0.04	0.02	0.000	0.00
10	6	9	-0.97	-0.30	0.97	0.30	0.000	0.00
11	7	10	0.34	0.11	-0.34	-0.11	0.000	0.00
12	8	11	1.37	0.39	-1.37	-0.39	0.000	0.00
13	9	13	-0.65	-0.21	0.65	0.21	0.000	0.00
14	10	11	0.74	0.26	-0.74	-0.26	0.000	0.00
15	10	12	0.66	0.20	-0.66	-0.20	0.000	0.00
16	11	13	2.14	0.66	-2.14	-0.66	0.000	0.00
						Total:	0.004	0.00

Table 27 - Initial Network Bus Data (5:30p.m -5:45p.m Period)

Bus Data						
Bus	Voltage		Generation		Load	
#	Mag(pu)	Ang(deg)	P (MW)	Q (MVAr)	P (MW)	Q (MVAr)
1	1.000	0.000*	10.25	3.11	-	-
2	1.000	-0.004	0.01	0.00	1.24	0.37
3	1.000	-0.006	0.00	0.00	0.46	0.14
4	0.999	-0.006	0.01	0.00	0.97	0.29
5	0.999	-0.006	0.01	0.00	1.45	0.44
6	0.999	-0.006	0.00	0.00	0.95	0.29
7	1.000	-0.006	0.16	0.05	2.28	0.69
8	1.000	-0.005	0.00	0.00	0.10	0.03
9	0.999	-0.006	-	-	0.92	0.28
10	1.000	-0.006	0.00	0.00	0.22	0.07
11	0.999	-0.006	0.62	0.19	0.14	0.04
12	0.999	-0.006	0.02	0.01	0.88	0.27
13	0.999	-0.006	-	-	1.48	0.45
		Total:	11.10	3.36	11.09	3.36

Table 28 - Initial Network Branch Data (5:30p.m -5:45p.m Period)

Branch Data

Brnch #	From Bus	To Bus	From Bus Injection P (MW)	From Bus Injection Q (MVAr)	To Bus Injection P (MW)	To Bus Injection Q (MVAr)	Loss (I^2 * Z) P (MW)	Loss (I^2 * Z) Q (MVAr)
1	1	2	6.19	1.81	-6.19	-1.80	0.001	0.00
2	1	7	4.06	1.30	-4.06	-1.30	0.001	0.00
3	2	4	3.42	1.01	-3.42	-1.01	0.001	0.00
4	2	8	1.54	0.42	-1.54	-0.42	0.000	0.00
5	3	7	-1.62	-0.55	1.62	0.55	0.000	0.00
6	3	10	1.17	0.41	-1.17	-0.41	0.000	0.00
7	4	5	1.14	0.34	-1.14	-0.34	0.000	0.00
8	4	9	1.31	0.38	-1.31	-0.38	0.000	0.00
9	5	6	-0.30	-0.10	0.30	0.10	0.000	0.00
10	6	9	-1.25	-0.38	1.25	0.38	0.000	0.00
11	7	10	0.32	0.11	-0.32	-0.11	0.000	0.00
12	8	11	1.44	0.39	-1.44	-0.39	0.000	0.00
13	9	13	-0.86	-0.29	0.86	0.29	0.000	0.00
14	10	11	0.42	0.20	-0.42	-0.20	0.000	0.00
15	10	12	0.85	0.26	-0.85	-0.26	0.000	0.00
16	11	13	2.34	0.73	-2.34	-0.73	0.000	0.00
						Total:	0.005	0.00

Table 29 - Initial Network Bus Data (5:45p.m -6p.m Period)

Bus Data

Bus #	Voltage Mag(pu)	Voltage Ang(deg)	Generation P (MW)	Generation Q (MVAr)	Load P (MW)	Load Q (MVAr)
1	1.000	0.000*	11.41	3.46	-	-
2	1.000	-0.005	0.01	0.00	1.42	0.43
3	1.000	-0.007	0.00	0.00	0.47	0.14
4	0.999	-0.006	0.01	0.00	0.96	0.29
5	0.999	-0.007	0.01	0.00	1.97	0.60
6	0.999	-0.007	0.00	0.00	0.94	0.29
7	1.000	-0.007	0.16	0.05	3.32	1.01
8	1.000	-0.005	0.00	0.00	0.11	0.03
9	0.999	-0.006	-	-	0.92	0.28
10	0.999	-0.006	0.00	0.00	0.23	0.07
11	0.999	-0.006	1.19	0.36	0.15	0.04
12	0.999	-0.007	0.02	0.01	0.87	0.26
13	0.999	-0.006	-	-	1.45	0.44
		Total:	12.83	3.89	12.82	3.88

Table 30 - Initial Network Branch Data (5:45p.m -6p.m Period)

Brnch #	From Bus	To Bus	From Bus Injection P (MW)	From Bus Injection Q (MVAr)	To Bus Injection P (MW)	To Bus Injection Q (MVAr)	Loss (I^2 * Z) P (MW)	Loss (I^2 * Z) Q (MVAr)
1	1	2	6.58	1.89	-6.58	-1.89	0.001	0.00
2	1	7	4.83	1.57	-4.83	-1.57	0.001	0.00
3	2	4	3.67	1.07	-3.67	-1.07	0.002	0.00
4	2	8	1.50	0.39	-1.50	-0.39	0.000	0.00
5	3	7	-1.40	-0.51	1.40	0.51	0.000	0.00
6	3	10	0.94	0.37	-0.94	-0.37	0.000	0.00
7	4	5	1.40	0.42	-1.40	-0.42	0.000	0.00
8	4	9	1.31	0.37	-1.31	-0.37	0.000	0.00
9	5	6	-0.57	-0.18	0.57	0.18	0.000	0.00
10	6	9	-1.51	-0.46	1.51	0.46	0.000	0.00
11	7	10	0.27	0.10	-0.27	-0.10	0.000	0.00
12	8	11	1.39	0.36	-1.39	-0.36	0.000	0.00
13	9	13	-1.11	-0.38	1.11	0.38	0.000	0.00
14	10	11	0.13	0.15	-0.13	-0.15	0.000	0.00
15	10	12	0.85	0.26	-0.85	-0.26	0.000	0.00
16	11	13	2.56	0.82	-2.56	-0.82	0.000	0.00
						Total:	0.006	0.00

Aiming to integrate this benefit of congestion reduction and line losses reduction, two additional factors were added to the fitness function (21), named Bus_Benefit (*BusB*) and Loss Benefit (*LossB*). This way the new fitness function of the problem becomes (22):

$$\mathrm{F}\,(x') = \mathrm{f}\,(x') + \sum_{j=1}^{J} g_i \,*\, R - BusB - LossB \qquad (22)$$

Bus Benefit and Loss Benefit is the way to measure how much the choice of certain services during market clearing will contribute to reducing network congestion and reducing energy losses. For this purpose, the simulation of the initial network presented in Tables 23 to 30 was performed in order to identify the initial power flow and establish parameters that will serve as a basis for calculating the benefits. Considering every period *t* from regulating power periods *R*, the maximum power value found at any bus in the initial test (PF_i) will be compared with the maximum value found after the decrease in consumption caused by the DR (PF_f) for every period $t \in R$, this difference will be multiplied by the benefit to the DSO (*BBen*) in running this market clearing. To calculate *LossB* the sum of all losses in the initial test (L_i) is compared with the sum after DR (L_f) and finally multiplied by the benefit to the DSO for every period $t \in R$. These benefits are calculated according to equations 22 and 23.

$$BusB \;=\; BBen \,*\, \sum_{t\,\in\,R} (PF_i \;-\; PF_f\,) \qquad (22)$$

$$LossB = LBen * \sum_{t \in R} (L_i - L_f) \tag{23}$$

In order to obtain the PF_i and L_i parameters, the network without the consumption decrease after the Market Clearing is simulated, as done previously in this subsection. Simulations in each of the regulating power periods indicate higher power flow between buses 1 and 2 in period of 17:45h to 18h thus the value of PF_i refer to this period and branch being equal to 6.58 MW. Initial Losses values L_i are 0.004, 0.004, 0.005 and 0.006 for periods *t* equal 5, 6 ,7 and 8 respectively.

Now that the new fitness function is defined, some of the EA used previously were applied to solve the problem. In this experiment, only the differential evolution (DE) variant DE/target-to best, the self-adaptive version of DE called HyDE-DF and the VS were selected, due to its success in the previous experiment. After this first study a sensibility analysis of some parameters is applied in order to identify its interference in the study as well as test different scenarios.

5.4.3. RESULTS ANALYSIS

In this subsection three algorithms are compared (DE/target-to best, HyDE-DF and VS) in order to compare their performances. To perform the experiments, the best values of *F* and *Cr* found for the two DE algorithms in subsection 5.2.3 were used again. So that the objective function is evaluated the same number of times for all algorithms, 10000 generations of individuals were performed. The population number *NP* of 10 was used. The convergence of the strategies over the generations is presented in Figure 20. The result becomes more negative throughout the iterations due to the minimization character of the study that continues. Again, in three cases the convergence rate is similar, they quickly slow down when near 500 generations with DE/target-to-best/1 faster than the other algorithms while VS was slower to converge. The three algorithms converge to very close results, the average convergence found in generation 10000 by DE/target-to-best/1 owns fitness of -2679.11, while fitness in HyDE-DF was -3015,73 and in VS was -2811,74. As the complexity of the problem increased, the results obtained were different when comparing the algorithms. In the previous experiments differential evolution algorithms obtained the best results while in this experiment HyDE-DF and VS found better solutions.

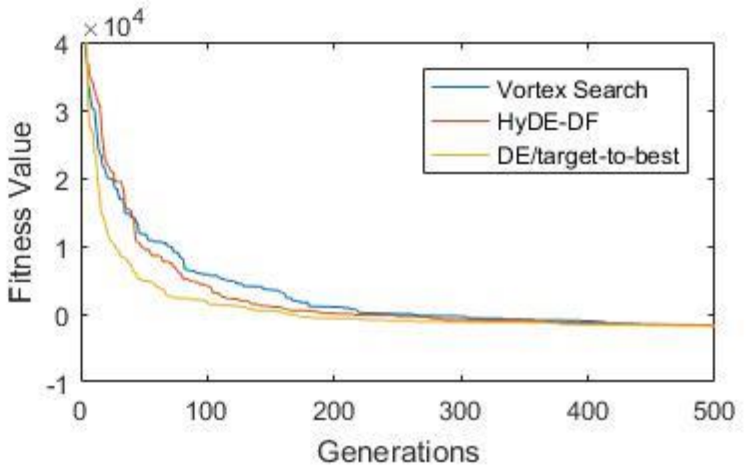


Figure 20 – Experiment 3: Convergence of each method

The results are shown in Table 31, in which the mean and standard deviation of the values obtained in 10 runs are presented for each algorithm. Due to running MATPOWER every iteration the t/Run (s) increased with each run during around 20 minutes.

Table 31 – Experiment 3: Results for each method (€)

Method	Fitness	Reserve Cost	Dispatch Cost	Benefits/Penalties	t/Run (s)
DE	-2679,11 ± 108,23	88,00 ± 101,11	-1521,6 ± 76,97	-1245,52 ± 129,73	1147 ± 37
Vortex	-3015,73 ± 98,64	263,72 ± 150,24	-1786,81 ± 691,88	-1492,64 ± 907,69	1150 ± 27
HyDE-DF	-2811,74 ± 64,28	190,4 ± 172,42	-1443,83 ± 189,76	-1558,31 ± 363,20	1210 ± 24

Figures 21, 22 and 23 were elaborated, they graphically demonstrate the best result obtained among all runs for DE/target-to-best/1, HyDE-DF and VS respectively. Figure 21 is related to the DE/target-to-best/1 9th run, which fitness is -2821,3 with RC = 100,0 and DC = -1510,0 and the part referring to benefit and penalties equal to -1411,26. As the previous experiments, a conditional service, *Cond2*, was selected in the market clearing. One block was selected of the thermostatically controlled loads aggregators, which is block *d1* from aggregator *c2*. Aggregator *i2* was cleared completely in all up-regulating periods while aggregator *i1 and i3* were activated alternatingly. DSO request was attended in all regulating periods while rebound limit was respected as well.

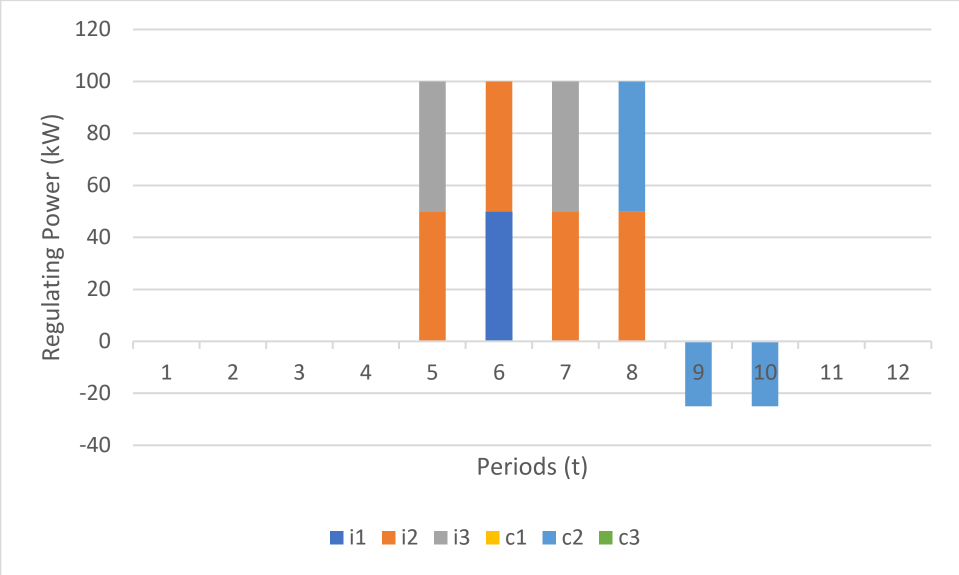


Figure 21 – Experiment 3: DE/target-to-best/1 Upward and Downward Regulation

Figure 22 is related to the HyDE-DF 9th run, which best fitness among all runs and algorithms, of -3151,1, was obtained. RC = 340,05 and DC = -1248,4 and benefit/penalties equal to -2242,75. Different from previous experiments, the scheduled service, *Sched*, was selected in the market clearing. Two blocks were selected of the thermostatically controlled loads aggregators, which are block *d2* from aggregator *c1* and block *d1* from aggregator *c2*. All conventional aggregators were cleared in the market up regulating periods as well as in some rebound periods. Due to the fact that block *d1* of aggregator c2 presents -30kW of rebound it was necessary to use the conventional aggregators in this period in order to respect the allowed rebound limit of 25kW.

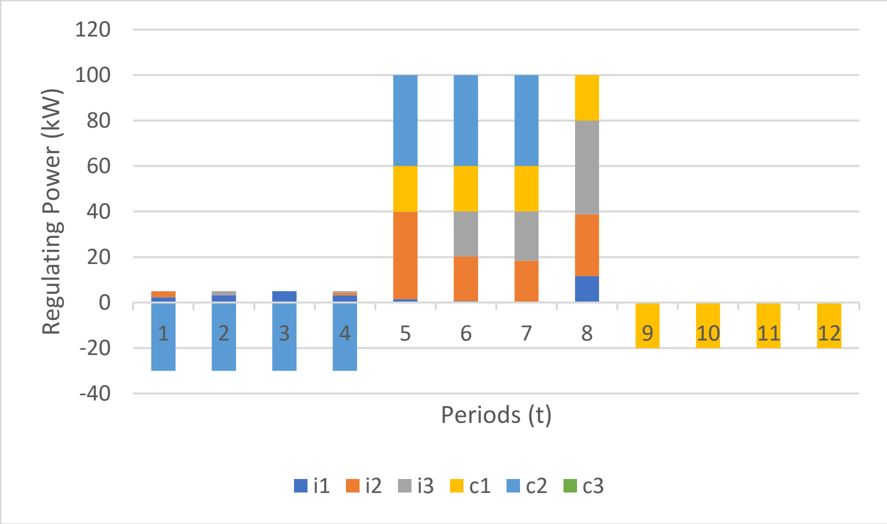


Figure 22 - Experiment 3: HyDE-DF Upward and Downward Regulation

Figure 23 is related to the VS 2nd run, which best fitness among all runs, of -2993,35 was obtained, with RC = 425,00 and DC = -1111,58 and benefit/penalties equal to -2306,78. As well as HyDE-DF algorithm the scheduled service *Sched*, was selected in the market clearing, but with two different blocks of the thermostatically controlled loads aggregators. Block *d1* from aggregator *c2* and block *d4* from aggregator *c3* were selected. Again, all conventional aggregators were cleared in the market up regulating periods, in order to reach the 100kW DSO request, as well as in some rebound periods to compensate the rebound in excess of what is permitted.

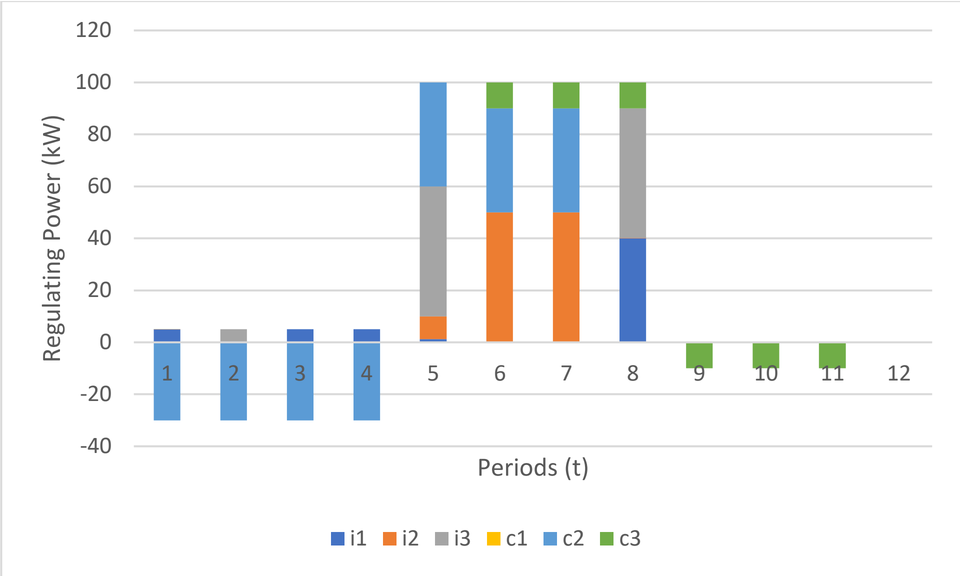


Figure 23 – Vortex Search Upward and Downward Regulation

5.5. EXPERIMENT 4: PARAMETERS SENSIBILITY ANALYSIS

In order to evaluate the impact of certain parameters on the final result obtained by the algorithms in Market Clearing, in this case study a sensitivity analysis was designed. This type of analysis seeks to estimate the result generated by changes in the parameters or activities of a procedure, thereby measuring the degree of sensitivity of the process to a change. In other words, in the sensitivity analysis, several different variables are tested to understand the effect that each one produces at the end of the process. For this study some of the variables from the previous study were changed individually and the DE/target-to-best/1 and HyDE-DF algorithms were used to find the solutions as well as the same number of generations, 10000, and *NP* of 10. Four parameters were identified as of interest for sensitivity analysis, these being the DSO request (D_{pt}^{Reg}), the allowed rebound (D_{pt}^{Reb}), the DR capacity of each aggregator (P_{pit}^{Con}) and the Bus Benefit (*BBen*). Table 32 details the variations used for each of these parameters in the tests.

Table 32 – Experiment 4 Sensibility Analysis Parameters

Sensibility Analysis Parameters

Changed Parameter	Variation				
	Value 1	Value 2	Initial Test	Value 3	Value 4
DSO REQUEST (kW)	50	75	100	125	150
REBOUND (kW)	0	12,5	1	37,5	50
DR CAPACITY (kW)	25	37,5	50	75	100
BUS (€)	200	400	800	1600	3200

5.5.1. DSO REQUEST SENSIBILITY ANALYSIS

The first sensitivity analysis test refers to the variation of the parameter (D_{pt}^{Reg}), its function is to indicate the amount of up regulation the DSO demands in the pre-established periods. In the initial study case, the demand was 100kW for each of the regulating periods, so this parameter was varied and simulated for values of 50, 75, 125 and 150 kW to verify how the variation of the DSO demand impacts the results obtained.

Table 33 presents the mean and standard deviation of the main values in the 10 runs performed by the DE/target-to-best/1 algorithm while Table 34 presents the results obtained using HyDE-DF algorithm. With the results it is possible to see that the best fitness values were found the lower the DSO request, this result can be explained by checking the reserve cost and dispatch cost values. Due to the fact that less energy is demanded while the parameters $C_p^{R,DSO}$ and $C_p^{D,DSO}$ regarding the DSO benefit remain unchanged, it created this difference in the fitness value when the lower demand for load reduction. Another important result is that the benefits related to the network reached in the experiment are better with 125 kW than with 150 kW of request. It is also important to note that for all levels of DSO Request the HyDE-DF algorithm found better solutions.

Table 33 – DE/target-to-best/1 DSO Request Sensibility Analysis Results (€)

DSO Request	Fitness	Reserve Cost	Dispatch Cost	Benefits/Penalties
50 kW	-3452,05 ± 253,36	-150,00 ± 83,66	-2138,3 ± 192,09	-1163,75 ± 509,57
75 kW	-2978,82 ± 117,70	36,12 ± 142,01	-1738,48 ± 285,45	-1276,46 ± 482,81
100 kW	-2679,11 ± 108,23	88,00 ± 101,11	-1521,6 ± 76,97	-1245,52 ± 129,73
125 kW	-2323,29 ± 135,12	278,13 ± 102,00	-1240,06 ± 88,57	-1361,38 ± 69,47
150 kW	-2385,91 ± 114,47	441,65 ± 109,17	-1882,43 ± 44,80	-945,13 ± 103,99

Table 34 – HyDE-DF DSO Request Sensibility Analysis Results (€)

DSO Request	Fitness	Reserve Cost	Dispatch Cost	Benefits/Penalties
50 kW	-3972,48 ± 91,53	5,51 ± 42,37	-1788,58 ± 53,37	-2191,42 ± 17,14
75 kW	-3457,11 ± 119,32	187,17 ± 41,55	-1455,65 ± 78,61	-2198,64 ± 30,27
100 kW	-2811,74 ± 64,28	190,4 ± 172,42	-1443,83 ± 189,76	-1558,31 ± 363,20
125 kW	-2729,87 ± 40,62	259,80 ± 70,97	-2370,23 ± 80,27	-619,44 ± 38,77
150 kW	-2418,86 ± 42,88	391,98 ± 61,29	-1042,01 ± 43,52	-1768,83 ± 46,69

Tables 35 and 36 were elaborated looking for demonstrate the best result obtained among all runs for each performed test. These tables present the best result, in which run it was obtained and the selected service and blocks. The best fitness value was found to be - with DSO request equal to 50kW for both algorithms, where its value is -4077.1 on the first run of DE/target-to-best/1 algorithm and -4113,7 on the fifth run of HyDE-DF. All three service types were selected in both tests, only blocks from aggregator *c1* were picked in the DE/target-to-best/1 test while aggregator *c2* was selected along *c1* in HyDE-DF.

Table 35 – DE/target-to-best/1 DSO Request Sensibility Analysis Best Run Results

DSO Request (kW)	50	75	125	150
Fitness Value (€)	-4077,1	-3098,5	-2492,2	-2554,2
Run	1	1	7	9
Zp	1	3	3	2
Selected Blocks	*c1 -> d3*	*c1 -> d3*	*2x c1 -> d1*	*c1 -> d3*

Table 36 - HyDE-DF DSO Request Sensibility Analysis Best Run Results

DSO Request (kW)	50	75	125	150
Fitness Value (€)	-4113,7	-3741,5	-2778,6	-2480
Run	5	4	3	6
Zp	1	1	2	3
Selected Blocks	*c2 -> d1*	*c1 -> d2* *c2 -> d1*	*c2 -> d1*	*c1 -> d2* *c2 -> d1*

Figures 24 and 25 were elaborated looking for demonstrate graphically the best result obtained among all runs for each performed test. It can be seen that the higher the DSO demand, the more diversified are the services and aggregators chosen. This can be noted easily in DE/target-to-best/1, because when the DSO request is equal to 50kW only 3 aggregators provide the service, being entirely responsible for the demand in the period, while in tests with higher DSO request the Market Clearing aggregator selection is more diversified and the risk of non-delivery is mitigated. In HyDE-DF this characteristic is less evident but can also be noted, while only three aggregators were selected in the test with a 50kW request, five aggregators were selected when the request was for 150kW.

Figure 24 - DE/target-to-best/1 DSO Request Sensibility Analysis Upward and Downward Regulation

Figure 25- HyDE-DF DSO Request Sensibility Analysis Upward and Downward Regulation

5.5.2. ALLOWED REBOUND SENSIBILITY ANALYSIS

The second sensitivity analysis performed refers to the variation of the parameter (D_{pt}^{Reb}), its function is to indicate the amount of rebound allowed by the DSO in the pre-established periods. In the initial study case, the allowed rebound was 25 kW for each of the rebound periods, in this test this parameter was varied and simulated for values of 0, 12.5, 37.5 and 50 kW to verify how the variation of the allowed rebound impacts the selection of services and the results obtained.

Table 37 presents the mean and standard deviation of the main values in the 10 runs performed by the DE/target-to-best/1 algorithm. It is interesting to note that varying this parameter does not cause much distortion in the fitness values obtained since they all remain around -2500 and -3000.

Table 37 – DE/target-to-best/1 Allowed Rebound Sensibility Analysis Results (€)

Rebound (kW)	Fitness	Reserve Cost	Dispatch Cost	Benefits/Penalties
0	-2597,50 ± 106,53	-107,12 ± 95,66	-1385,6 ± 53,98	-1319,00 ± 133,21
12,5	-2758,85 ± 93,31	-112,80 ± 91,39	-2447,74 ± 36,80	-423,91 ± 128,39
25	-2679,11 ± 108,23	88,00 ± 101,11	-1521,6 ± 76,97	-1245,52 ± 129,73
37,5	-2970,34 ± 83,01	325,91 ± 176,35	-1440,76 ± 502,63	-1855,49 ± 724,49
50	-2799,71 ± 158,44	153,51 ± 116,42	-1691,93 ± 185,12	-1261,29 ± 352,66

Table 38 presents the mean and standard deviation of the main values in the 10 runs performed by the HyDE-DF algorithm. Again, it is noted that varying this parameter does not cause much distortion in the fitness values obtained. Another important remark is that for all values, but $D_{pt}^{Reb} = 50kW$, HyDE-DF reached better solutions.

Table 38 – HyDE-DF Allowed Rebound Sensibility Analysis Results (€)

Rebound(kW)	Fitness	Reserve Cost	Dispatch Cost	Benefits/Penalties
0	-2648,94 ± 84,93	-202,56 ± 138,92	-1311,3 ± 182,67	-1540,2 ± 235,90
12,5	-2837,46 ± 44,58	119,89 ± 63,95	-2502,07 ± 40,86	-455,28 ± 34,94
25	-2811,74 ± 64,28	190,4 ± 172,42	-1443,83 ± 189,76	-1558,31 ± 363,20
37,5	-3234,73 ± 145,79	344,61 ± 40,77	-1309,13 ± 95,40	-2270,21 ± 32,85
50	-2351,64 ± 132,01	465,91 ± 108,84	-965,71 ± 167,25	-1851,84 ± 145,18

Tables 39 and 40 presents the best result, in which run it was obtained and the selected service and blocks for both algorithms. The best fitness value found by DE/target-to-best/1 was -3149.6 on the first run with D_{pt}^{Reb} = 50kW. In this run three blocks were selected, block *d1* from aggregator *c1* two times and block *d2* from aggregator *c3*. Again, all three service types were selected as well as blocks from aggregators *c1*, *c2* and *c3* were utilized.

Table 39 – DE/target-to-best/1 Allowed Rebound Sensibility Analysis Best Run Results

Rebound (kW)	0	12,5	37,5	50
Fitness Value(€)	-2727,1	-2869,3	-3093,2	-3149,6
Run	8	10	1	1
Zp	3	2	1	1
Selected Blocks	*x*	*x*	*c2 -> d1* *c3 -> d1*	*2x c1 ->d1* *c3 -> d2*

HyDE-DF found the best solution of -3423.0 on the third run with D_{pt}^{Reb} = 37.5 kW. In this run three blocks were selected, block *d1* from aggregator *c1* two times and block *d1* from aggregator *c2*. Again, all three service types were selected as well as blocks from aggregators *c1*, *c2* and *c3* were utilized demonstrating the feasibility of participation of all aggregators in the market.

Table 40 - HyDE-DF Allowed Rebound Sensibility Analysis Best Run Results

Rebound (kW)	0	12,5	37,5	50
Fitness Value(€)	-2777,9	-2893,5	-3423	-3319
Run	6	10	3	1
Zp	3	2	1	1
Selected Blocks	*x*	*c2 -> d1*	*2x c1 -> d1* *c2 -> d1*	*c1 ->d1* *c2 -> d1* *c3 -> d1*

Figure 26 was elaborated looking for graphically demonstrate the best result obtained by DE/target-to-best/1 among all runs for each performed test. Due to the rebound limitations when $D_{pt}^{Reb} = 0\,kW$ and $D_{pt}^{Reb} = 12{,}5\,kW$ only conventional aggregators were selected. On the other hand, when the allowed rebound was bigger than the initial case, the reached fitness value was greater and more blocks from thermostatically controlled loads aggregators were selected.

Figure 26 – DE/target-to-best/1 Allowed Rebound Sensibility Analysis Upward and Downward Regulation

Figure 27 was elaborated looking for graphically demonstrate the best result obtained by HyDE-DF among all runs for each performed test. Due to the rebound limitations when $D_{pt}^{Reb} = 0\,kW$ only conventional aggregators were selected while when $D_{pt}^{Reb} = 12{,}5\,kW$ conventional aggregators were activated in the rebound periods in order to compensate the excessive rebound. When the allowed rebound was bigger than the initial case, solutions obtained were greater with more diversity of aggregators selection and more blocks from thermostatically controlled loads aggregators utilized.

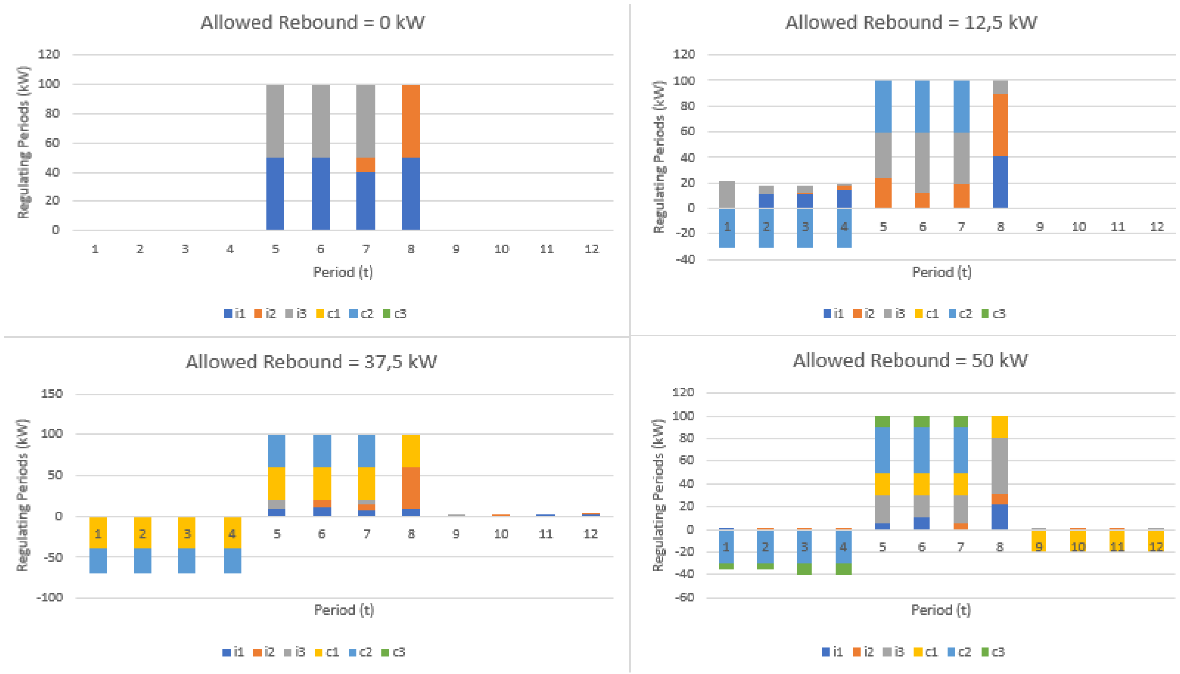


Figure 27 - HyDE-DF Allowed Rebound Sensibility Analysis Upward and Downward Regulation

5.5.3. DR Capacity Sensibility Analysis

The third sensitivity analysis performed refers to the variation of the parameter P_{pit}^{Con} , its function is to indicate the amount of load reduction each conventional aggregator i can deliver in each period. In the initial study case, the maximum load reduction each aggregator could provide per period was 50 kW, in this test this parameter was varied and simulated for values of 25, 37.5, 75 and 100 kW to verify how this the variation impact the selection of services and the results obtained.

Tables 41 and 42 presents the mean and standard deviation of the main values in the 10 runs performed by algorithms DE/target-to-best/1 and HyDE-DF respectively. In relation to the fitness values obtained it is noted that no major variations occur as well as in reserve cost values. Meanwhile, there were significant variations in Dispatch Cost and Benefits that offset each other and did not significantly change the fitness value.

Table 41 – DE/target-to-best/1 DR Capacity Sensibility Analysis Results (€)

DR Cap.(kW)	Fitness	Reserve Cost	Dispatch Cost	Benefits/Penalties
25	-2726,25 ± 75,07	255,10 ± 68,91	-1663,37 ± 63,47	-1317,99 ± 60,29
37,5	-2724,74 ± 82,06	176,53 ± 103,95	-2468,36 ± 459,46	-432,92 ± 556,45
50	-2679,11 ± 108,23	88,00 ± 101,11	-1521,6 ± 76,97	-1245,52 ± 129,73
75	-2610,92 ± 124,60	38,44 ± 39,47	-2471,95 ± 113,09	-177,41 ± 102,00
100	-2769,48 ± 50,93	5,03 ± 15,09	-1503,98 ± 77,04	-1270,25 ± 123,25

Table 42 - HyDE-DF DR Capacity Sensibility Analysis Results (€)

DR Cap.(kW)	Fitness	Reserve Cost	Dispatch Cost	Benefits/Penalties
25	-3077,08 ± 46,85	455,15 ± 29,15	-1228,83 ± 31,98	-2303,40 ± 8,68
37,5	-3009,55 ± 113,68	341,71 ± 141,88	-1624,15 ± 660,45	-1727,11 ± 858,73
50	-2811,74 ± 64,28	190,4 ± 172,42	-1443,83 ± 189,76	-1558,31 ± 363,20
75	-2966,3 ± 110,52	177,64 ± 124,81	-2195,6 ± 641,89	-948,33 ± 855,11
100	-2929,14 ± 90,11	263,73 ± 145,33	-1291,46 ± 239,99	-1901,42 ± 411,36

Table 43 presents the best results obtained among all runs of DE/target-to-best/1. The best fitness value found was -2869.6 on the third run with P_{pit}^{Con} = 37,5 kW. In this run service *Cond2* was selected along with block *d1* from aggregator *c2*. This time, *Sched* service was not selected in any of the best runs while blocks from all aggregators were delivered.

Table 43 - DE/target-to-best/1 DR Capacity Sensibility Analysis Best Run Results

DR (kW)	25	37,5	75	100
Fitness Value(€)	-2766,8	-2869,3	-2818,9	-2809,3
Run	3	3	5	8
Zp	3	2	2	3
Selected Blocks	*c2 -> d2* *c3 -> d3*	*c2 -> d1*	*c1 -> d1*	-

Table 44 presents the best results obtained among all runs of HyDE-DF. The best fitness value found was -3182.4 on the second run with P_{pit}^{Con} = 37,5 kW. In this run, different from DE/target-to-best/1, service *Sched* was selected along with blocks *d2* and *d1* from aggregators *c1* and *c2* respectively. This time, *Cond1* and *Cond2* services were not selected in any of the best runs while blocks from aggregator *c3* were not cleared.

Table 44 - HyDE-DF DR Capacity Sensibility Analysis Best Run Results

DR (kW)	25	37,5	75	100
Fitness Value (€)	-3121,1	-3182,4	-3174,8	-3180,1
Run	2	2	4	10
Zp	1	1	1	1
Selected Blocks	*2x c1 -> d2* *c2 -> d1*	*c1 -> d2* *c2 -> d1*	*c1 -> d2* *c2 -> d1*	*c1 -> d2* *c2 -> d1*

Figure 28 was elaborated looking for graphically demonstrate the best result obtained among all DE/target-to-best/1 runs for each performed test. The interesting analysis of this sensibility case is that due to the load reduction limitations when $P_{pit}^{Con} = 25\ kW$ blocks *d2* from aggregator *c2* and *d3* from aggregator *c3* were selected so the DSO request is satisfied. While, when the $P_{pit}^{Con} = 100\ kW$ only conventional aggregators were delivered to satisfy the DSO demand.

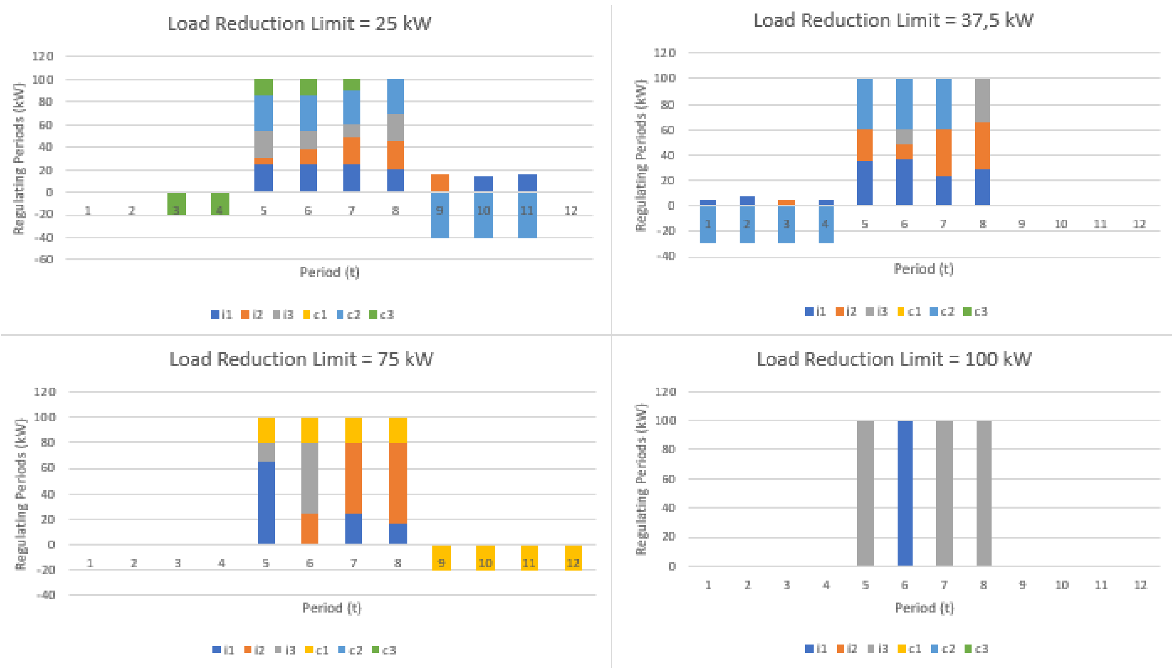


Figure 28 – DE/target-to-best/1 DR Capacity Sensibility Analysis Upward and Downward Regulation

Figure 29 was elaborated looking for graphically demonstrate the best result obtained among all HyDE-DF runs for each performed test. Again, due to the load reduction limitations of conventional aggregators when $P_{pit}^{Con} = 25\ kW$, blocks from thermostatically controlled loads aggregators were necessary cleared in order to satisfy the DSO request. Different from DE/target-to-best/1, HyDE-DF selected thermostatically controlled loads aggregators when $P_{pit}^{Con} = 100\ kW$ and reached better results.

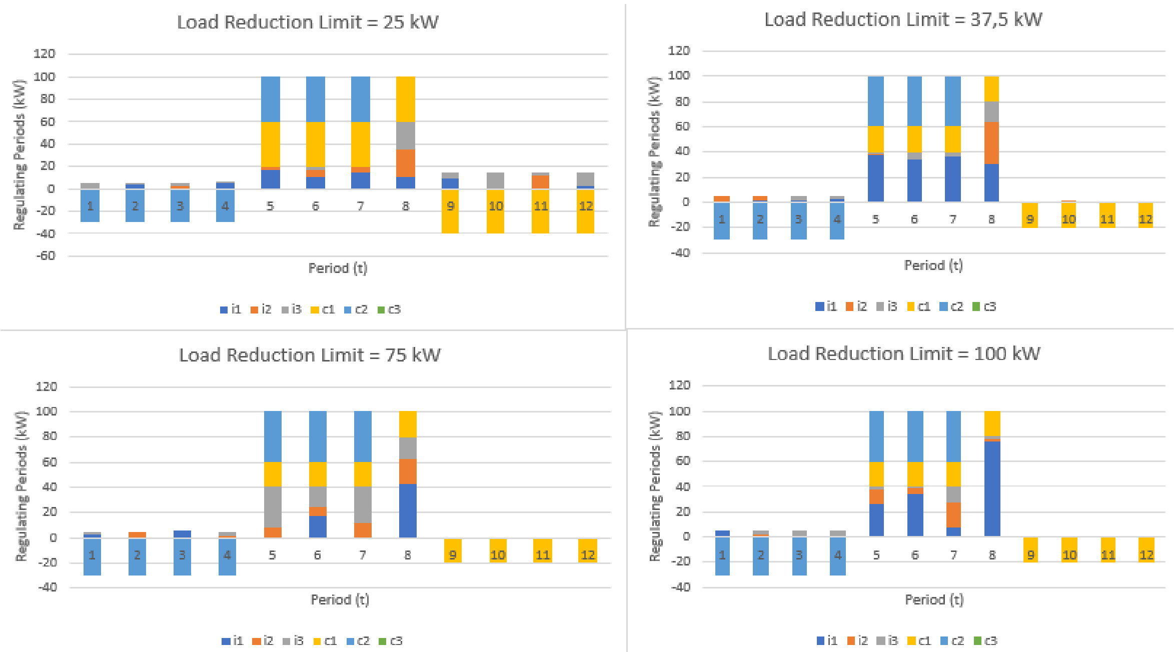


Figure 29 - HyDE-DF DR Capacity Sensibility Analysis Upward and Downward Regulation

5.5.4. Bus Benefit Sensibility Analysis

The fourth and final sensitivity analysis performed refers to the variation of the parameter *BBen*, its function is to quantify the benefit to the distribution network by delivering the DR. In the initial study case *BBen* was equal 800, in this test this parameter was varied and simulated for values of 200, 400, 1600 and 3200 to verify how this the variation impact the selection of services and the results obtained.

Tables 45 and 46 presents the mean and standard deviation of the main values in the 10 runs performed by the DE/target-to-best/1 and HyDE-DF algorithms respectively. It can be seen from the results that the variation of this parameter causes large changes in the fitness value because this variation causes great variation in the benefit/penalty values making the other parameters impact reduced.

Table 45 – DE/target-to-best/1 Bus Benefit Sensibility Analysis Results (€)

Bus Benefit	Fitness	Reserve Cost	Dispatch Cost	Benefits/Penalties
200	-1094,74 ± 78,30	57,97 ± 96,33	-1509,24 ± 67,34	356,52 ± 89,26
400	-1615,15 ± 104,82	83,71 ± 91,30	-1579,69 ± 105,19	-119,17 ± 171,12
800	-2679,11 ± 108,23	88,00 ± 101,11	-1521,6 ± 76,97	-1245,52 ± 129,73
1600	-5090,25 ± 83,15	188,99 ± 114,93	-2445,6 ± 438,35	-2846,4 ± 530,49
3200	-9698,72 ± 110,56	222,20 ± 99,56	-2458,13 ± 440,77	-7462,80 ± 527,88

Table 46 – HyDE-DF Bus Benefit Sensibility Analysis Results (€)

Bus Benefit	Fitness	Reserve Cost	Dispatch Cost	Benefits/Penalties
200	-1303,16 ± 111,88	377,12 ± 92,72	-1277,55 ± 169,36	-452,72 ± 273,52
400	-1615,15 ± 104,82	296,36 ± 153,66	-1626,13 ± 612,41	-285,38 ± 741,57
800	-2811,74 ± 64,28	190,4 ± 172,42	-1443,83 ± 189,76	-1558,31 ± 363,20
1600	-5287,53 ± 99,33	320,23 ± 150,53	-1619,75 ± 662,99	-3988,01 ± 859,76
3200	-9820,57 ± 128,18	373,35 ± 101,78	-1261,25 ± 179,99	-8932,35 ± 357,76

Table 47 presents the best results obtained among all runs of DE/target-to-best/1. The best fitness value found was -9871.1 on the tenth run with *BBen* = 3200. In this run service *Cond1* was selected along with blocks *d1* from aggregator *c2* and *c3*. This time again *Sched* service was not selected in any of the best runs while blocks from all aggregators were delivered. It was noticed that *BBen* value has a great impact in the fitness value and service selection.

Table 47 – DE/target-to-best/1 Bus Benefit Sensibility Analysis Best Run Results

Bus Benefit (€)	200	400	1600	3200
Fitness Value(€)	-1187,1	-1717,4	-5250,4	-9871,1
Run	6	6	5	10
Zp	3	3	2	2
Selected Blocks	*x*	*x*	*c1 -> d1* *c2 -> d2*	*c2 -> d1* *c3 -> d1*

Table 48 presents the best results obtained among all runs of HyDE-DF. The best fitness value found was -10024.0 on the third run with *BBen* = 3200. In this run service *Sched* was selected along with blocks *d1* from aggregator *c1* and *d2* from aggregator *c2*. This time, totally different from DE/target-to-best/1 simulation, only the *Sched* service was selected in the best performance among the runs while *Cond1* and *Cond2* were not present. It was noticed that besides the best performance service being always the same, the choice of blocks followed the same trend with blocks *d1* and *d2* from aggregators *c1* and *c2* being cleared in the market.

Table 48 - HyDE-DF Bus Benefit Sensibility Analysis Best Run Results

Bus Benefit (€)	200	400	1600	3200
Fitness Value(€)	-1449,6	-2038,1	-5471,4	-10024
Run	3	3	7	3
Zp	1	1	1	1
Selected Blocks	*c1 -> d1* *c2 -> d2*	*c1 -> d1* *c2 -> d2*	*c1 -> d1* *c2 -> d2*	*c1 -> d1* *c2 -> d2*

Figures 30 and 31 were elaborated looking for graphically demonstrate the best result obtained among all runs for each performed test. The interesting analysis of this sensibility test is that for *BBen* equal 200 and 400 the best result was exactly the same and only conventional aggregators were chosen while for *BBen* 1600 and 3200 the variety of selection was bigger and in rebound periods conventional aggregators were activated. While this activation aggregates in the costs of the market clearing, it was necessary in order to guarantee the allowed rebound limits.

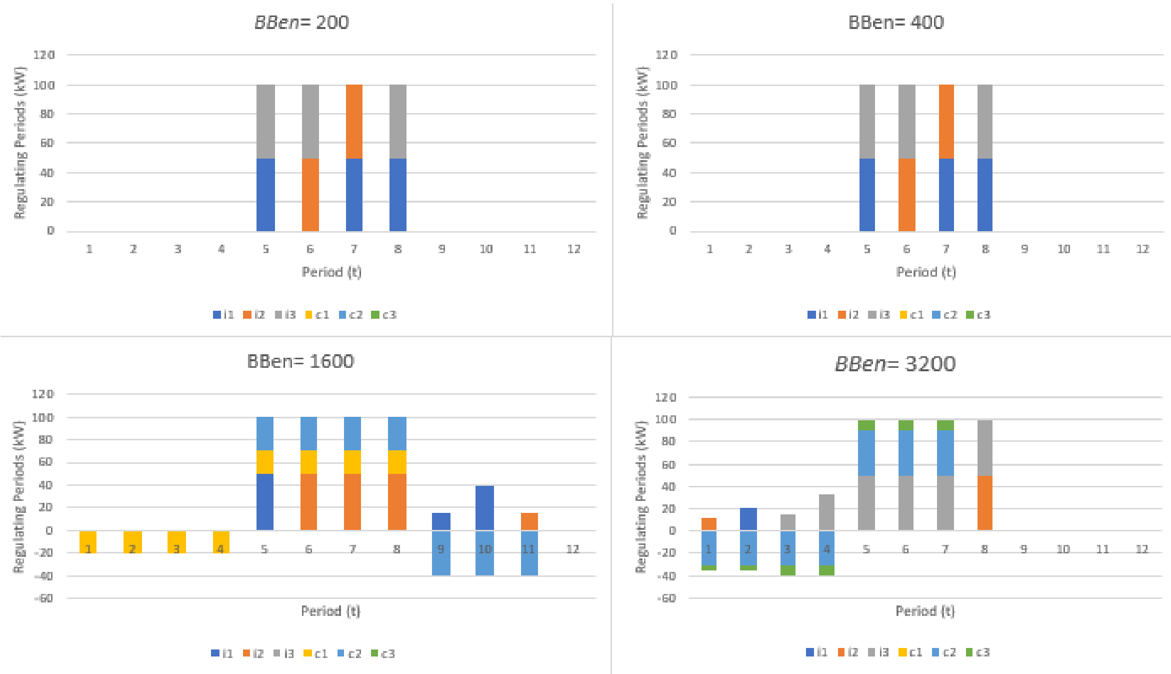


Figure 30 – DE/target-to-best/1 Bus Benefit Sensibility Analysis Upward and Downward Regulation

Figure 31 - HyDE-DF Bus Benefit Sensibility Analysis Upward and Downward Regulation

5.6. CASE STUDY FINAL REMARKS

In the proposed LEM, the best combination of bids and offers must be found so the equilibrium price is reached and the participants adequate their products in order to decrease the costs and maximize profits. In experiment 1 the impact of the DE parameters using the DE/rand/1 and DE/target-to-best/1 algorithms were analyzed to know the best combination of these for carrying out the tests. In the second part, tests were made, and the results obtained from the optimization problem were collected. Assessing the impact of each of the DE parameters tests were formulated whose intention was to identify the best combination of the parameters *F*, *Cr*, *NP* and *G* for DE/rand/1 and DE/target-to-best/1. Three tests were performed, the first of which referring to the parameters F and Cr, the second referring the *NP* parameter and the third to the number of generations (G). $F = 1$ for both algorithms and $Cr = 0.2$ and $Cr = 0.1$ for DE/rand/1 and DE/target-to-best/1 respectively were the best parameters reached. $Np = 70$ and $G = 3500$ were the best-found parameters as well. After that, other algorithms such as VS, HyDE and HyDE-DF were used to offer a comparison of performance. Analyzing, DE algorithms converged faster and to better results. The purpose of Experiment 2 was to identify the difference in the Market Clearing results and test the scalability of the algorithms when adding aggregators and their offers to the market. DE/rand/1 and VS converged faster than the others algorithms tested and DE algorithms found better fitness values. Compared to experiment 1 all algorithms obtained better results.

In Experiment 3, a 13-bus distribution network with a 30MVA substation and several distributed generation units was considered. The objective of this study was considering the addition of the BISITE mockup model network to the previous problem. To perform this experiment a new fitness function was formulated. With respect to the results DE/target-to-best/1 converged faster than the other algorithms while VS was slower to converge. HyDE-DF has obtained the best result among the algorithms. By again reaching good results the goal of adding the network was achieved. In Experiment 4, four parameters were identified as of interest for sensitivity analysis, these being the DSO request (D_{pt}^{Reg}), the allowed rebound (D_{pt}^{Reb}), the DR capacity of each aggregator (P_{Con}^{Up}) and the Bus Benefit (*BBen*). In order to evaluate the impact of certain parameters on the final result obtained by the algorithms in Market Clearing, this case study measured the degree of sensitivity of the process by changing the parameters. After the tests was identified that *BBen* and D_{pt}^{Reg}, while the parameters D_{pt}^{Reb} and P_{Con}^{Up} show a lower sensitivity.

6. CONCLUSIONS

This chapter presents the conclusions of this work. Section 6.1 exhibit the developed work and highlight the contributions and conclusions about it. Section 6.2 presents some limitations of the work as well as some ideas for future developments of the case studies presented in the Thesis.

6.1. CONTRIBUCTIONS AND CONCLUSIONS

The work done in this dissertation focused on studying the use of flexibility in LEMs and the way these products can be transformed into services to solve problems in the distribution network. In this case, the objective of the work was to present the state of the art of the changes that have been occurring in the energy markets, the factors that led to these changes and, finally, to present solutions such as LEM and to test a model by means of case studies. Overall, it was concluded that LEMs are a great way to integrate RER and load flexibility and that several prerogatives and roles should be defined in the formulation of a LEM. Furthermore, it was found that evolutionary algorithms have great value and can be a good alternative in simulating Market Clearing in LEMs that may demand large computational capacity.

Initially, in order to contextualize the problem, the concepts of DG and load flexibility as well as their different types and categories were presented. Next, the possible problems faced by distribution networks due to the large penetration of DG were presented as well as the direct and indirect methods feasible to solve the problem. One of the methods presented is the LEM, it was presented why this idea seeks to integrate DG, flexibility and the end-user's greater participation in the market in an economical and efficient manner. Then in chapter 3 the LEM concept was detailed in order to elucidate its proposal and present possible benefits and barriers to be faced when adopting this type of market. Next, several prerequisites that must be analyzed when implementing an LEM in order for it to be operational were elucidated. Finally, the various stakeholders involved in the market were presented in order to show the services they can offer, their role in the market, and the interactions among them in the context of LEM.

In the first experiment, different DE strategies were used to execute a flexibility contract market in a proposed LEM model. Tests of DE parameters, *F*, *Cr* and *NP*, were accomplished to verify their influence in the obtained results and subsequently to use the best combination of them. With this analysis, it can be seen that the choice of parameters significantly impacts the results obtained. Also, it can be concluded that each DE strategy has a different set of optimal parameters that lead to good performance. After that, DE algorithms were compared with other algorithms, namely VS, HyDE and HyDE-DF, to compare the results obtained and the convergence time to the best solutions. In the comparison, better fitness values were obtained with the tuned DE strategies than with the self-parameter tuning algorithms, with similar execution times for all of them. Despite its good performance, the tested algorithms were not able to reach the optimal fitness value found by the linear method. Then in the second experiment two more aggregators were added to the market in order to increase competition in the market and to test the scalability of the algorithms. It was verified that the addition of new aggregators was beneficial to the solution of the problem, all algorithms tested obtained better solutions when compared to experiment 1 and converged quickly.

Regarding experiment 3 there was an expansion of the problem with the addition of a distribution network to the model. By adding this network its parameters were defined, as well as the interaction of the aggregators with the network and finally the fitness function of the problem was adjusted in order to consider the benefits of DR to the network. With the execution of the tests, it was confirmed the viability of using the evolutionary algorithms to perform the market clearing even with the increase of the problem's complexity since all of them quickly converged to optimal solutions. Finally In Experiment 4 the sensitivity test of the parameters was performed, resulting in the identification of a high sensitivity for the parameters *BBen* and D_{pt}^{Reg}, while the parameters D_{pt}^{Reb} and P_{Con}^{Up} show a lower sensitivity. In relation to the performance of the algorithms, there were changes in the pattern as the experiments progressed with DE algorithms reaching better results in the experiments 1 and 2 while in experiments 3 and 4 when the problem was more complex HyDE-DF and VS performed better. Finally, it can be stated that the objectives proposed in Section 1.2 were achieved since the simulations went well and good results were obtained.

6.2. LIMITATIONS AND FUTURE WORK

LEM is a topic with a lot of interest in view of the need for change in the energy markets. In this way the work developed can be the target of future improvements in order to obtain more realistic and accurate results. In order to improve the work some modifications, tests and additions can be made, such as:

- Use actual values regarding aggregator costs, energy costs, DSO benefits, etc. In order to make the simulation closer to reality.
- Create new types of aggregators and services offered in order to make the market more complete.
- Use a larger and more detailed city, with more charging stations and a differentiated focus on V2G service.
- Expand the scalability test and simulate the market clearing with many more aggregators.
- Improve decision method that defines in which bus the aggregator will decrease energy consumption.

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Appendix – Case Study: List of Variables and Parameters

i	Conventional aggregator
c	Thermostatically controlled load aggregator
t	Period
d	Asymmetric block offer
$\mathrm{R}C_p$	Reserve cost (€)
DC_p	Dispatch cost (€)
P_p	Daily probability of activation of the service *p*
P_{pit}	Conventional aggregator upward regulation (kW)
P_{pit}^{Con}	Conventional aggregator upward regulation upper limit (kW)
Q_{pcdt}^{DR}	Block *d* response at each time *t* (kW)
s_{pt}	Amount of rebound at each time *t* (kW)
z_p	Binary variable that indicates which of the services has been selected
m_{pcd}	Indicate which block *d* is selected
B_{pcd}^{DR}	Number of granular blocks
$C_{pit}^{R,Con}$	Reserve component cost (€/ kW) for unit *i* to meet service *p* at time *t*
$C_{pcd}^{R,DR}$	Reserve cost of the block *d* (€)

$C_{pt}^{R,\mathrm{Reb}}$	Reserve cost per kW of rebound (€/ kW)
$C_{p}^{R,DSO}$	Reserve component DSO Benefit (€)
$C_{pit}^{\mathrm{D},Con}$	Dispatch component cost (€/ kW) for unit *i* to meet service *p* at time *t*
$C_{pcd}^{\mathrm{D},DR}$	Dispatch cost of the block *d* (€)
$C_{p\mathrm{t}}^{\mathrm{D,Reb}}$	Dispatch cost per kW of rebound (€/ kW)
$C_{p}^{\mathrm{D},DSO}$	Dispatch component DSO Benefit (€)
D_{pt}^{Reg}	DSO up-regulation requirement at each time *t* (kW)
D_{pt}^{Reb}	Allowed rebound at each time *t* (kW)
$BusB$	Bus benefit clearing the market (€)
$LossB$	Loss benefit clearing the market (€)
PF_i	Maximum power flow value from the initial test (kW)
PF_f	Maximum power flow value after market clearing (kW)
$BBen$	Bus benefit factor
L_i	Power losses from the initial test (kW)
L_f	Power losses after market clearing (kW)
$LBen$	Loss Benefit Factor
NP	DE Population Number
G	DE Number of generations
F	DE mutation operator

Cr	DE recombination operator