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Operation of PV-Battery Analysis in Microgrids Considering Different Demand Response Programs

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Resumo

Todos os anos, o número de recursos energéticos distribuídos (DER) integrados na rede elétrica de energia aumenta, como é o caso de unidades de produção, principalmente de origem renovável, sistemas de armazenamento de energia e ainda programas de resposta à procura (DR). Este aumento deve-se às preocupações ambientais, que têm vindo a ter um maior impacto na geração de energia a nível global. Deste modo, surge a necessidade de aumentar a flexibilidade do sistema, uma vez que os recursos renováveis apresentam incerteza, tornando-se difícil a sua previsão.

Para aumentar esta flexibilidade da rede, serão aplicadas diferentes estratégias. Serão utilizados programas de resposta à procura associados a um agregador de DR, os quais os consumidores do tipo residencial, comercial ou industrial poderão integrar nos seus tarifários. Os programas DR poderão ser à base de incentivos (IBDR) ou poderão ser à base do preço onde os preços da energia elétrica promovem a um maior consumo nas horas fora do pico de consumo. O agregador de DR tem como função, aglomerar todas as propostas de procura e venda de energia de todos os consumidores que associados aos diferentes programas de DR. Depois vende o DR obtido a compradores que poderão ser o operador independente do sistema (ISO) de energia.

Para além disso, será integrado no modelo, uma fonte de produção de energia solar fotovoltaica juntamente com um sistema de baterias de armazenamento de energia de forma a maximizar o lucro do agregador de DR maximizando a fiabilidade e eficiência do sistema de produção de energia elétrica bem como aumentar a flexibilidade da rede. Com a introdução dos programas de DR bem como as unidades de geração de origem renovável e ainda sistemas de armazenamento de energia do lado do consumidor, o sistema elétrico de energia torna-se cada vez mais descentralizado, possibilitando que o consumidor tenha influência direta no preço da energia elétrica.

Por último, será aplicado um modelo de Otimização Robusta (RO) de forma a considerar a incerteza de produção solar fotovoltaica no modelo. A aplicação deste método aproximará o modelo da realidade uma vez que a produção solar fotovoltaica apresenta uma natureza incerta devido às variabilidades das condições atmosféricas bem como devido à sazonalidade. Estas variações terão um impacto no lucro do agregador de DR bem como no funcionamento de todo o modelo que serão abordadas neste trabalho.

Palavras-Chave: Produção Solar Fotovoltaica; Sistema de Armazenamento de Energia; Agregador de Demand Response; Optimização robusta; Rede Inteligente.

Abstract

Every year, the number of distributed energy resources (DER) integrated into the power grid increases, such as generation units, mainly of renewable origin, energy storage systems and also demand response (DR) programs. This increase is due to environmental concerns, which have been having a greater impact on global power generation. Thus, arises the need to improve the system flexibility, since renewable resources present uncertainty, making it difficult to forecast them.

To increase this grid flexibility, different strategies will be applied. Demand response programs associated with a DR aggregator will be used, which residential, commercial or industrial consumers can integrate into their tariffs. DR programs can be incentive-based (IBDR) or they can be price-based where electricity prices promote greater consumption in off-peak hours. The function of the DR aggregator is to aggregate all the offers for demand and sale of energy from all the consumers associated with different DR programs. Then, it sells the obtained DR to buyers that could be the Independent System Operator (ISO) of the Power System.

In addition, a solar photovoltaic power generation source will be integrated into the model along with an energy storage battery system in order to maximise the profit of the DR aggregator maximising the reliability and efficiency of the power generation system as well as increasing the flexibility of the grid. With the introduction of DR programs as well as generation units of renewable origin as well as energy storage systems on the consumer side, the power system becomes more and more decentralized, enabling the consumer to have a direct influence on the price of electricity.

Finally, a Robust Optimization (RO) model will be applied in order to consider the uncertainty of solar PV production in the model. The application of this method will bring the model closer to reality since solar PV production presents an uncertain nature due to the variability of atmospheric conditions as well as due to seasonality. These variations will have an impact on the profit of the DR aggregator as well as the operation of the whole model which will be addressed in this paper.

Keywords: Solar Photovoltaic Generation; Energy Storage System; Demand Response Aggregator; Robust Optimization; Smart Grid.

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Bruno Ramos

*“Those who dream by day are cognizant of many things
which escape those who dream only by night.”*

Edgar Allan Poe

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Abbreviations

AMI	Advanced Metering Infrastructure.
AS	Ancillary Services.
BESS	Battery Energy Storage System.
BIPV/T	Building Integrated Photovoltaic and Thermal.
CAP	Capacity Market Program.
CPLEX	C programming language.
CPP	Critical Peak Pricing.
DB	Demand Bidding.
DER	Distributed Energy Resource.
DG	Distributed Generation.
DLC	Direct Load Control.
DMS	Demand Side Management.
DR	Demand Response.
DRO	Demand Response Option agreement.
EDRP	Emergency Demand Response Program.
EMS	Energy Management System.
ESS	Energy Storage System.
EESS	Electrical Energy Storage System.
EV	Electrical Vehicles.
FDR	Fixed Demand Response.
GAMS	General Algebraic Modelation System.
GHG	Greenhouse-gas.
HVAC	Heating, Ventilation and Air Conditioning.
IBDR	Incentive-Based Demand Response.
I/C	Interruptible/Curtailable.
ICT	Information and Communication Technology.
ISO	Independent System operator.
LP	Linear Programming.
MG	Microgrid.
MILP	Mixed-integer linear programming.
OF	Objective Function.
PBDR	Price-Based Demand Response.
PCI	Projects of Common Interest.
P2G	Prosumer-to-Grid.
P2P	Peer-to-Peer.
PV	Photovoltaic.
PV/T	Photovoltaic Thermal.
RO	Robust Optimization.

RER	Renewable Energy Resource.
RES	Renewable Energy Source.
RTP	Real-Time Pricing.
SOC	State-of-Charge.
TOU	Time-of-use.
UN	United Nations.
V2G	Vehicle-to-Grid.
VPP	Virtual Power Plant.
WHO	World Health Organisation.

Nomenclature

Indices

t	Time index
j	Index of reward-based DR steps
p	Index of time periods
c	Consumer index
f	Fixed DR contract index
b	Index Related with fixed DR contract block
op	Index related with DR option agreement

Scalars

P_{dch}^{max}	maximum power discharged from BESS at each time index t [kW].
P_{ch}^{max}	maximum power charged to BESS at each time index t [kW].
SOC^{max}	maximum value for the energy accumulated in the BESS [kWh].
SOC^{min}	minimum value for the energy accumulated in the BESS [kWh].
η^{ch}	Power charge efficiency of the BESS.
η^{dch}	Power discharge efficiency of the BESS.
a	initial percentage of the SOC^{max} in the BESS.
$SOC^{initial}$	initial SOC of the BESS [kWh].
α	tolerance of PV generation for RO in percentage.
Γ	uncertainty budget for RO of PV generation.

Parameters

$PF(t)$	consumers participation probability in the reward-based DR program.
$D_0(c,t)$	Initial demand related to consumer c in time interval t.
$E(c,t,p)$	Elasticity related to consumer c in time interval t related to the price in period p.
$\lambda_0(c,p)$	Initial price related to consumer c in period p.
$\lambda(c,p)$	TOU price related to consumer c in period p.
f_{op}^{pen}	penalty related to rejection of DR agreement [MWh].
$\overline{P}_j^{DR}(t)$	load reduction step in reward-based DR [MWh].
$\overline{R}_j^{DR}(t)$	Given reward in reward-based DR [\$/MWh].
$P_{pv}^{max}(t)$	Maximum PV generation for each time interval t for RO [kW].
$P_{pv}^{min}(t)$	Minimum PV generation for each time interval t for RO [kW].
$P_{pv}^{avg}(t)$	PV array with all values of PV generation for all time intervals obtained from the average of 20 PV generation scenarios [kW].

Variables

z	objective function for the DR aggregator profit maximization [$].
$TOU(t)$	Obtained TOU volume from consumers within time interval t [MWh].
$\lambda_{f,b}^{DR}$	Fixed contract price of DR [$].
λ_{op}^{DR}	Agreement price on DR options [$].
$P_{f,b}^{DR}(t)$	Fixed DR contracted power for each time interval t [MWh].
$P_{op}^{DR}(t)$	DR options agreement power for each time interval t [MWh].
$P_{ch}(t)$	Power charged to the BESS at each time interval t [kW].
$P_{dch}(t)$	Power discharged from the BESS at each time interval t [kW].
$SOC(t)$	State-of-charge of the BESS [kWh].
$P_{pv}(t)$	PV power generation at each time interval [kW].
P_{pv}^{Total}	Total PV generation during one day [MW].
$\beta, \xi(t)$	dual variables for the RO.
$y(t)$	auxiliary variable for RO.

Binary Variables

$v_j^{DR}(t)$	Binary variable for reduced load step level in reward-based DR.
$v_{op}^{DR}(t)$	Binary variable for application of DR option aggrement.
$u_{ch}(t)$	Binary variable indicating the charging mode of the BESS.
$u_{dch}(t)$	Binary variable indicating the discharging mode of the BESS.
$x(t)$	Binary variable for the application of RO model.

Chapter 1

Introduction

This chapter presents an overview about the work that will be developed for this thesis. First of all, it is shown the framework of the problem and also the motivation that originated the interest to develop this work, in order to contextualize the theme. Next, the methodology used in the resolution of this thesis and goals that are supposed to get from this. Finally, the display of the dissertation structure and notation that will be used.

1.1 Framework

Climate change is a huge environmental problem that humanity has been fighting against. According to the 2030 Agenda for Sustainable Development of the United Nations (UN) [1], the environmental challenges to be faced are diverse. This global action plan adopted in 2015 proposes concrete measures to achieve a fairer, more prosperous and greener world within ten years.

Global warming induced by Greenhouse Gas (GHG) emissions, which according to the UN have increased by 50% since 1990, which is possible to see in Figure 1.1, is accelerating climate changes, threatening the survival of thousands of people, animals and plants, due to catastrophic weather episodes , increasingly frequent and extreme, such as fires and floods. Therefore, one of the main objectives, which was stipulated in the Paris agreement is to contain the increase in the global average temperature, below 2 ºC, in order to minimize these phenomena [2].

Another huge problem, addressed by the World Health Organization (WHO), is air pollution. The WHO estimates that 90% of the world's population breathes polluted air and consequently requires a reduction in contamination to reduce the rate of respiratory diseases, with the objective to avoid thousands of deaths every year [3].

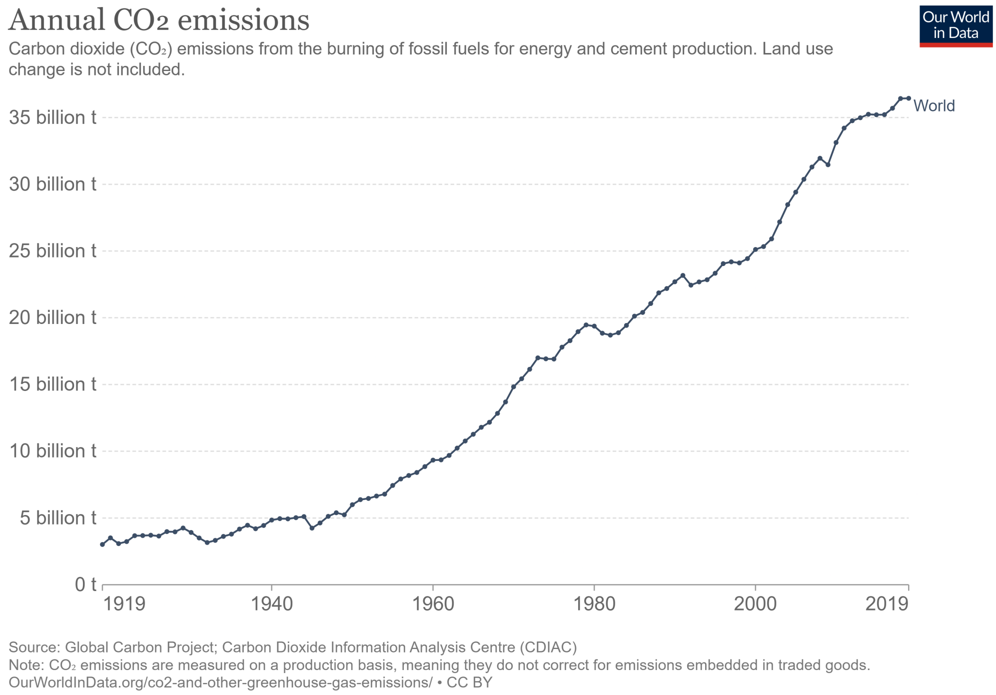

Figure 1.1: Carbon dioxide (CO_2) emissions from the burning of fossil fuels for energy and cement production [4].

Water pollution is also a huge problem for all living beings, so there is a need to eliminate waste discharges, minimize the use of chemicals and treat more wastewater. The energy production is responsible for around 60% of the global GHG emissions. The United Nations (UN), estimates that 13% does not have access to electricity and that fossil fuels are supplying around 3 billion people for daily use. Because of this situation, the energy system requires an energy transition to a cleaner, more accessible and efficient model based on renewable resources to increase the sustainability and resistence of the communities to the environmental problems of the actuality [4].

The power sector is in a global transition. This is a result of the necessity to reduce the greenhouse-gas emissions. Over the past decade, the cost of renewable energy systems (RES) has dropped significantly. Solar power had a drop by almost 80% and wind power by 40%, making both of them economically competitive with the conventional power sources, such as coal and natural gas. As a result, renewable energy resources are in a fast growing process of utilization.

For each country reach the Paris agreement objectives stipulated, resulted a large investment in renewable energy resources (RER) to insert in the power systems, this is a great solution to achieve the agreement objectives and mainly to reduce the damage that fossil fuels are doing to our planet [5].

The conventional power grid is structured in a model that the energy is produced in large amount and centralized power generation plants in the upstream grid. Than the this huge amount of energy is provided to the consumer using long transmission and distribution lines. The believed idea was that the larger power plants were built, more efficient the electricity system became.

For a long time, that logic was considered as the best possible but with the urgent need to reduce the GHG emissions, resulted in a greater investment in RERs. However, the intermittent nature of RERs, is a big setback for the centralized model of the power grid and with the increase need to have a clean power system, RERs are installed in the grid close to the consumers in other to reduce the losses in transmission and distribution, originating a decentralized power grid. In Figure 1.2, is schematized the difference between the conventional, centralized power system and the future decentralized power system.

Therefore, the generation of electricity energy in smaller amounts, closer to end-users and using renewable energy resources can dramatically increase energy efficiency, reduce CO_2 emissions, improve grid resiliency and reduce the need for new transmission system investments [6].

Because of the characteristic shared among all the renewable sources, their variability, introduce uncertainty in the power system so became difficult to predict the energy generation from renewable energies like solar or wind, this happens due to the unpredictability of weather conditions.

In the solar photovoltaic (PV) generation case, the variability and unpredictability of generation brings a problem for it integration in the grid. The variability of this resource, may lead to excess or lack of power generation comparative to the consumer demand. As a result, PV generation intalled alone in the grid have a low level of reliability and efficiency [7].

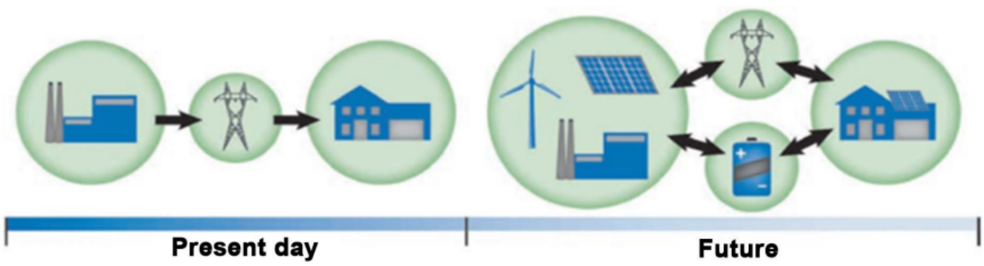

Figure 1.2: Transition of the power grid system [8].

To increase the penetration level of distributed generation, such as solar PV generation, energy storage systems (ESS) are a good solution to deal with the renewable energy resources (RER) uncertainty. Combining storage with PV generation, helps the energy system to achieve the balance between demand and power generation.

At the periods when the PV power generation is greater than the demand from the consumer, the ESS is charged with the surplus of energy. If the PV power generation is lower than the demand, the ESS discharge power to balance the system. This solution brings reliability and flexibility to the PV generation system [7].

Solar generation was one of the renewables that had an higher development. The solar energy generation have been exponentially increased their share on global energy production which is possible to observe in Figure 1.3. This is a consequence of the huge decrease of PV panels modules prices in the last years, represented in Figure 1.4, and also because of the decrease of the batteries prices, which makes that their penetration on the grid together with PV easier.

Another solution to increase the reliability and flexibility of RERs is the integration of demand response programs (DR). Demand response programs are also an incentive for the investment in renewable technologies, they are used to maintain the affordability and stability of the system by operators, at peak periods of demand, of DER generation or electricity price. The consumers enrolled in these programs have full control of their loads becoming an active part of the power grid operation.

DR programs integration, reduce the network congestion, the risk of black outs, the risk to compromise the system security and the GHG emissions. In addiction, they improve market economic efficiency, providing the maximum use of the existing generation systems and in some times, avoiding the need for new investments in generation [9, 10].

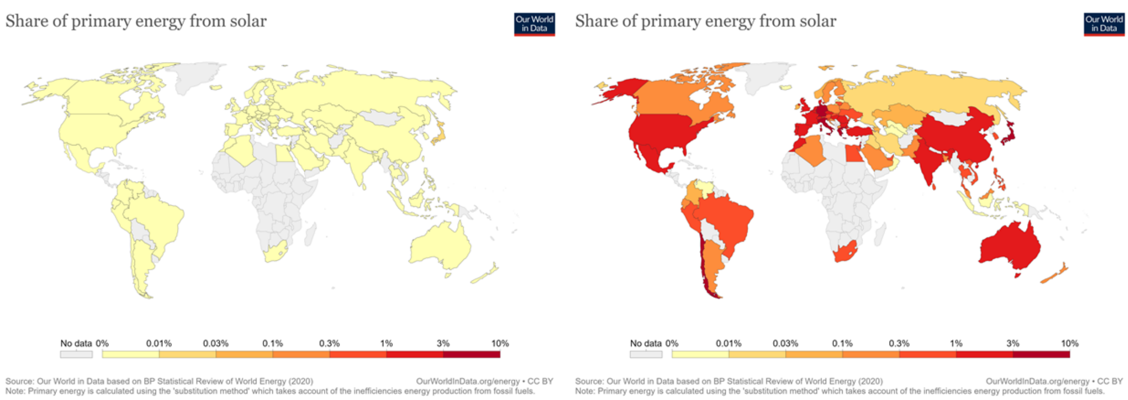

Figure 1.3: Share of primary energy from solar in years 2000 (left) and 2019 (right) [11].

Figure 1.4: Solar PV module price through the years [11].

To incentive the participation of consumers in DR programs, mainly at the residential level, a DR aggregator is implemented, that offers to customers different types of DR contracts that they could use. Then the DR aggregator participates in the energy market by making contracts with the purchaser of DR that could be the independent system operator (ISO). The DR aggregator group all the demands of all consumers that are participating in DR programs and sell it to the purchaser.

All these tecnologies that are presented here such as, solar PV generation, electrical energy storage system (ESS), demand response programs and DR aggregators are approached in this work with the objective of increasing the profit of DR aggregator, and in order to, create a simulation of a smart grid modelation for power and DR exchanges between the Energy market and the consumers through a DR aggregator that could be used on grids, microgrids or smart grids.

With the adoption of the Renewable Energy Directive and the Energy Efficiency Directive [12], have been formulated an idea that consumers have to be motivated to increase their energy use efficiency. So having the power to regulate the load demands, consumers play an active role to achieve the climate and environmental goals [13]. The consume and generation flexibility is essential to achieve a smart and sustainable energy system.

Short-term markets are essential for the integration of RERs into the energy system. Thus, the consumers can participate in these markets through DR programs, allowing them to adjust their consumption according to the program used. Bringing autonomy to the consumers, they can manage their own load in order to reduce their electricity bill making a more efficient use of the energy inside of the flexibility limits of their loads. For this the integration of smart meters is really important [13].

Smart metering systems, smart appliances and home automation are technological improvements that are being implemented in the energy system. These technologies, together with specific regulatory is essential to safeguard the legal position of consumers in their active participation. However, regulatory changes are delayed comparative to the available technology [14].

This new role of the consumers need to be defined through specific legal rules. For consumers who wants to be producers of energy for self-consumption or to supply it flexibility to the grid, need to endorse in electricity supply contracts with dynamic prices linked to the spot market, and new market players such as prosumers need to be allowed to operate on the energy markets [14].

Electric vehicles (EV), may be an important active agent of the future smart grids. With the installations of connecting points for charge or discharge EV batteries, that may be at consumers houses, or in parking lots, it is possible to use the batteries of EV when connected to the grid (V2G) to supply some loads when the generation is not enough, compensating the EV owner with some incentives or simply getting benefits for energy at on peak hours when the price is higher and buying at off peak hours when the price is lower.

In addition to that V2G connection DR programs help to overcome some uncertainty of participation, due to their capacity to incentive participation from the consumers because of the profitable price difference between the on peak and off peak period or because of the reward that EV owners may receive [15].

1.2 Motivation

This work was developed in order to solve some challenges that the penetration of RER inflicts in the grid. The main RER that is approached in this thesis is the solar PV, so how this renewable energy resource is integrated in the grid? Because of the uncertainty nature of this RER, resulted from the weather variability it is inserted another problem to minimize the impacts of this uncertainty in the grid so, which strategies are used to compensate PV generation uncertainty in order to increase the reliability of the grid and balance between demand and supply?

In addiction, in this work the energy storage systems have an huge role to solve some of the problem imposed by PV generation, so how is the behavior of the ESS when integrated together with a PV generation system? Another question that motivates the development of this work is about DR program, Which is the role of these programs for the consumer? and how these programs can be more attractive to the consumers? Finally, how this model developed could be applied in the future smart grids and Which are the challenges to do that?

1.3 Methodology

The work presented in this dissertation is related to the introduction of PV and BESS in the consumer side of the grid and the impacts that will have in the profit of a DR aggregator that may be implemented in a microgrid in order to bring together all the DR from the consumer and sell it to the purchaser that can be independent system operators, to participate in the energy market.

The model developed has as objective maximize the DR aggregator profit with the inclusion of PV generation and BESS at the consumer side. To do that, given a PV generation scenario, the code will reach to the best feasible solution for the DR aggregator of PV-battery-consumer power exchanges interactions and also with the purchaser (ISO) in order to maximize the profit. In addiction, it was studied 3 different cases for the model, the first one just considering the DR programs, the second one considering DR programs and the BESS and finaly, the case 3 that considerate DR programs, PV generation and BESS.

Furthermore, it is made a study about the PV generation uncertainty using Robust optimization programming in order to observe the impacts of the uncertainty solar photovoltaic generation resulted of the weather conditions uncertainty or season of the year. This work was developed using the program, General Algebraic Modeling System (GAMS) [16], and for the results treatment it was used Microsoft Excel and MATLAB.

1.4 Dissertation Structure

This dissertation is composed by 5 chapters, introduction, state-of-the-art, model design, numerical results and conclusion. In Chapter 2, is introduced the state of the art of that support this thesis. Firstly, is approached the definitions and developments of microgrids and smart grids in order to understand the actual state of transition of the power grids with the integration of RER and some of the important actors of these grids, like prosumers, EV owners, etc.. Secondly are presented the active actors of the grid, in this case the solar PV resource and ESS, in which is approached some of the recent technologies and some of the projects and researches in both areas.

Further, it was analyzed the DR programs that could be grouped by a DR aggregator, and approached the different types of DR programs present in market nowadays. In addiction, is studied the robust optimization (RO) program, in order to understand the concept for post application in the deterministic model developed. Finally some of similar works to mine are referenced in order to understand the type of work that was developed and compare it with other works in the area

In Chapter 3, is approached the design of the model developed and how the DR aggregator interacts with all system participants. In addiction the mathematical formulation for the model is presented in order to understand how the code was developed.

Chapter 4, starts with the presentation of the data preparation, that was used in the developed model in order to easily understand the behaviour of the system, followed by the results extracted and processed from the model that was ran in GAMS and then, the graphics was obtained using MATLAB.

Finally, in chapter 5, is presented the conclusions and final thoughts for the work developed and data results obtained and also some of the possible future works that could be development based on this thesis.

1.5 Notation

This dissertation uses the same notation used in scientific literature, and it is written accordingly with the English standards. Figures and tables are organized according to the chapter that they are presented, restarting numeration at the start of each chapter, they are numbered as "X.X" with the first "X" representing the chapter number and the second one the table or figure number. The same happens with the equations that are presented in this work like "(X.X)". The references that support this dissertation are identified as [XX]. The acronyms, follow the technical information and name abbreviation to the English standard and the nomenclature presented is referenced to the model mathematical formulation.

Chapter 2

State of the art

This chapter will present the theoretical and practical state of the art in microgrids, photovoltaic generation, electrical energy storage systems, and demand response programs, providing a perspective of the current technological panorama in the field of the renewable energy.

Firstly, the chapter allows a short review of the evolution, in the last years, of the distributed energy resources in terms of technological, legislation, and data evolution, to measure the impact of these technologies in the world of the power systems.

Afterward, further information is presented about recently approaches proposed in the scientific community, considering the PV generation, battery energy storage systems implementation in the grid, and the usage of DR response programs currently under research and development. Then, an overview of the robust optimization problem is briefly presented.

2.1 Microgrid

Microgrids are assumed to be a group of energy sources, that can be renewable or from fossil fuel, and loads located and interconnected, in order to form a grid that is connected as a single entity to the main electric grid. The microgrids are essential to improve the sustainability, resilience and energy efficiency of the electrical system, due to their ability to operate in isolated mode, which means that it is capable to work disconnected from the main grid ensuring the power supply of the loads [17].

This capacity is also useful, when is needed to supply a region with no access to the main grid, very common situation in the developing countries where the power transmission system is not available or is too unreliable.

An example of that application is in reference [18], where is compared the application of a microgrid of the type Wind/Diesel Generator/Battery-powered with the extension of the main grid in a village of Cape Town, South Africa which had no access to electricity energy.

To reach success with the microgrid, is essential to balance the generation with load. The penetration of renewable resources, increases the problems with the balance between the production and load, due mainly to the unpredictability of this type of resources. To solve these problems, energy storage is integrated as the element responsible to achieve balance between supply and demand. [17].

To evaluate power flows and to balance power generation with consumption, microgrids use information and communication technology (ICT), such as sensors and smart meters, creating energy management systems (EMS). An EMS is capable of monitoring and controlling power generation units and loads in order to make the grid operating in safety and improving the quality of power supply using hardware and software appropriated [19]. These concept of microgrid, fully equipped with smart technologies and with DERs is the base for a larger future smart grid which are approached in the next section.

2.2 Smart Grid

Smart Grids are intelligent technological platforms capable to monitoring and optimising the power supply flow in electricity grids, autonomously and automatically, with the inclusion of ICTs, such as sensors and smart meters, adjusting them according to changes in electricity demand and supply, using local EMS. In addition, they ensure the management of equipment and facilities, as well as the maintenance of the power grid.

The development of an intelligent grid, brings a large amount of challenges, requiring the harmonisation of energy industry and information and communication systems. These systems and telecommunications must ensure safe and efficient integration of the various components of a smart grid [20], as referenced in the last paragraph, smart meter, active demand management, distribution of generated energy, automatic network management and development of electric mobility.

Smart grids with the help of sensors that continuously assess the operation of electric grid, balancing loads and preventing breakdowns. Together with smart meters, smart grids provide information of consumption to energy suppliers and consumers in real time. With access to this information, consumers can adjust their consumption habits taking into account the different energy prices through the day, consuming more energy at cheaper hours to save money on their bills, so suppliers are able to adjust their services provided to the needs of consumers [21].

Due to the investments in renewable energy sources and to optimising energy efficiency automation, smart grids use all available technologies and information to improve the reliability and electricity quality reducing operation costs [22].

The actual state of transition of the power system, many challenges arise. Although, part of the solution is the implementation of smart grids, to a future objective to implement them in smart cities [23], but it is a lengthy and costly process due to the need to invest in new infrastructure and equipment. So, a smart grid may be equipped with a great variety of DER, as local power generation with renewable energy resources, energy storage, demand response programs and technology to monitoring and control all of that integrated DERs in order to maximize the grid reliability and efficiency [21]. A great step for increase the quality of a smart grid is the integration of smart houses in the grid.

This solution results in the democratization and decentralization of the energy sector, where the consumer gain a decisive role, being able to be a consumer and producer of electricity (prosumers). There are some investments for part of the EU under the Trans-European Networks for Energy (TEN-E) that aim to help integrate renewable energy in the power grid and to test the operation of smart grids, in order to complete the European energy market and allowing consumers to better regulate their energy consumption.

2.2.1 Prosumers

Prosumer are defined as "an energy user who generates renewable energy in its domestic environment and either store the surplus energy for future use or trades to interested energy customers in smart grids" [24].

Prosumers are different than the conventional energy consumers, the main difference is that the consumers just consume energy that is provided from the grid, the prosumer can produce their own energy with the integrated DER and store the excess of production if they are equipped with an ESS to future use. In some cases, when the price of electricity compensate, they sell their excess of production to generate profits [25].

To obtain an optimal management of energy, prosumers are equipped with smart meter and integrate these devices with others efficient applications, as household energy management systems [26], energy storage systems, electric vehicles, and vehicle-to-grid (V2G) systems. These systems all together integrated in the grid compound the smart houses, which have an beneficial impact in terms of efficiency and reliability of the smart grid [27]. Prosumer based smart grids offer an enhanced operation of household appliances using smart devices and communication technologies, offering storage capacity to manage power fluctuations, improving the balance between the demanded and supplied energy.

Comparative to conventional grids, prosumers smart grids, prosumers integration, improve the efficiency of the energy system. With this approach passive consumers shift to active prosumers maximize the economic, operational, and environmental benefits of the grid, using generation, demand reduction, demand response, data management and energy storage to achieve that objective [28].

Because of their active role in the grid, prosumers offer flexibility to the energy market by managing their energy generation and consumption in to the optimal solution and providing decentralized storage capacity. The energy market with prosumers is composed by consumers that provide services to the grid become an active actor of the grid. Prosumers can be integrated into the energy markets through different strategics of engagement [25].

First, peer-to-peer (P2P) model, which is compound by a flexible, autonomous and decentralized P2P network where prosumers are connected with each other directly [29]. In addiction, prosumer-to-grid (P2G) model, [30], is another way to integrate prosumer in the energy market, the prosumer is able to provide services to a microgrid in island mode, or connected to the main grid. Finally, organized prosumer group consist in multiples groups of prosumers that work together in order to have a pool large enough to form a prosumer virtual power plant (VPP), combined with a P2P platform to attain the advantages of each model [31].

2.2.2 Electric Vehicles

The development of EVs is in a slow phase yet. This is a result of the high manufacturing costs and also, the low state of development of charging facilities grid around the world. With the objective to boost the development of EVs utilization, many policies and regulations are been implemented, in order to make the EV in the future, the main transportation source for world population. It is projected, by International Energy Agency (IEA) that in 2030 the global EV population may reach nearly 130 million. A lot of challenges will arise with the large adoption of EVs, to the actual power system. Power quality degradation and transformers overloaded will be negative results with the integration of EV charging in the grid [32].

In order to minimize the negative impacts of the unmanaged loads that results from the EV charging in the grid, Vehicle-to-Grid (V2G) technology may be a welcome solution. It provides an effective and economic solution to introduce that additional demand in the grid, with minimum impact. This strategy, uses bidirectional flow of energy between the battery of the EV and the grid. Hence, it the surplus power during off peak periods can be stored in the EV battery and injecting this stored energy back to grid during on peak periods, to achieve the balance between demand and supply of electricity in the grid, increasing the grid flexibility and reliability.

Considering this concept, EV battery are no longer just loads that are linked to the grid, but also have the same function as a distributed energy storage system. As in the prosumer case, EVs shift from passive actors to active actor of the power grid. Moreover, EVs owners could profit from rewards in order to incentive the EV owners to accept being part of this strategy, and also to compensate the disadvantage of degradation of the EV battery that would be a harm of the discharging requirements.

In Figure 2.1, is shown a schematic of the V2G concept, for plug-in electrical vehicles (PEV), using a PEV aggregator possibility the participation of the PEV owners in the electricity market that is linked to the utility grid.

2.2.3 Smart Grid Projects

To implement a cross-border energy infrastructure in the EU, with the objective to interconnect the Power markets and grids of all members of EU there are some projects that are being developed with the purpose to solve the challenges that are involved with objective. This smart grid projects have impact on energy markets and market integration, and are identified as Projects of Common Interest (PCI). Some of the involved projects are presented in the next paragraphs [33].

- **SINCRO.GRID**

  In 2014, both Croatia and Slovenia transmission and distribution systems operators start to search for solutions to solve the low flexibility of their grids in order to possibility the integration of decentralized RERs. The implementation of this project will increase the reliability and security of the demand supply that is affected by the integration of renewable energy sources. [34]

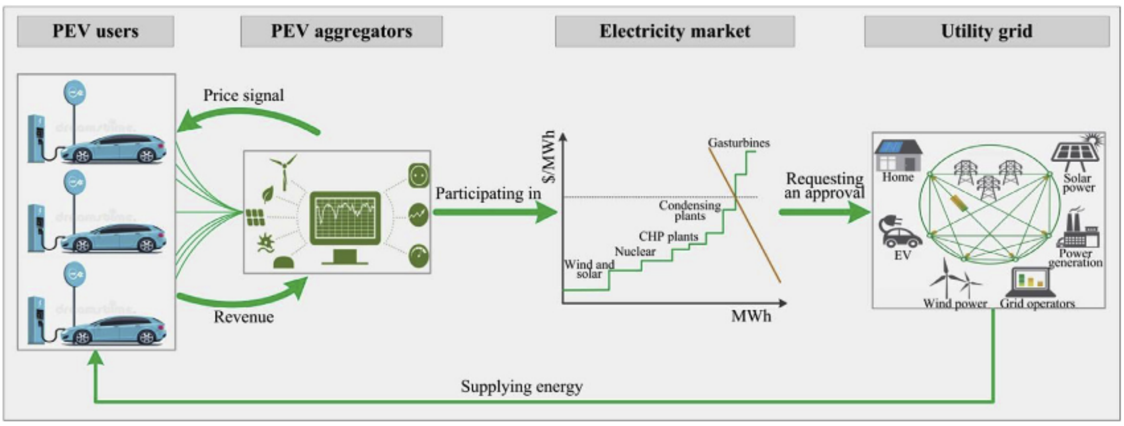

Figure 2.1: General framework for decentralized scheduling method for PEV [32].

- **Smart Border Initiative**

  In order to support the energy transition and European market integration of their cities, France and Germany are connecting policies. A smart grid that connects France to Germany will be design and implemented. This will insert flexibility and energy efficiency to the grid, to better integrate renewable energy resources. The main objective is to provide a cost effective strategy to improve the security of the grid and encourage the investment in RERs [35].

- **Danube inGrid**

  The objective of this project is to increase the integration of RER on the distribution grid by an optimal management with the application of smart technologies keeping the security and quality of power supply to the consumers in EU region. It will take in consideration the behaviour of the consumers, prosumers and generators connected to the network. This project is applied in Northwest of Hungary and West of Slovakia [36].

- **ACON**

  This project has as objective the faster integration electricity markets of Czech Republic and Slovakia. In order to achieve an economically efficient and sustainable electricity system with high quality of supply and low losses together with the integration of actions and behaviour of the users and also renewable energy resources. Further, this project aims to interconnect markets in the EU region securing the borders connection quality and using smart grid technologies in both countries. [37].

2.3 Solar Energy

2.3.1 Solar PV Generation Technology

Crystalline silicon is the main material used for wafer-based cells of first generation PV panels, that is represented in Figure 2.2. These panels consist on a single p-n junction, where the positive and negative type semiconductors form a junction area. The negative charges are presented in the doped negative (n) material layer and positive charges in the doped positive (p) material layer. This circulation of charges between layers creates a electric field at the junction, which photo generated charge carriers are pushed out of the P-n junction toward the electrodes [38].

In the early stages, PV technology went to a slow development until the oil crisis in the early 1970s. Since, renewable energies were object of an huge attention to find an alternative to fossil fuels. In early 1990s, was a turning point in the PV technology history, due to, some biding agreements resulted from the international concern on sustainability, in order to reduce the GHG in the atmosphere. PV technology have zero carbon emissions during operation which is an huge advantage comparative to conventional generation technologies [39].

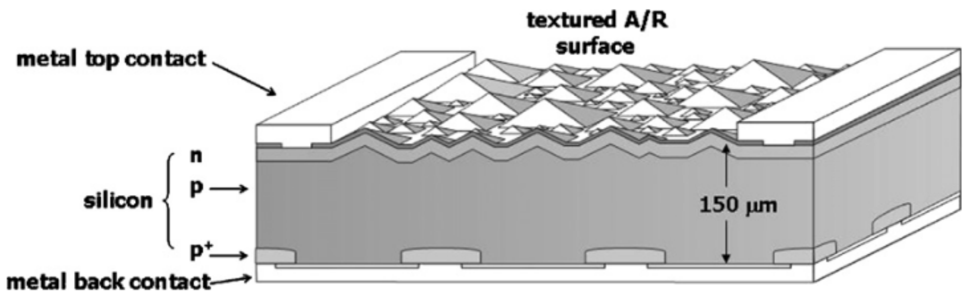

Figure 2.2: Single silicon crystal solar cell schematic [38].

Promising to overcome some of the limitations that first generation where subjected, surged the second generation of PV panels in the 1980s. This new generation pv cells uses a more diverse quantity of materials, such as, amorphous silicon cells, cadmium tellurium, etc.

The solar technology is been attracting many new markets, because of their unique, versatile nature and mainly because of their actual low cost. Throughout the years the added PV generation volume is increasing in a lot of countries. In all Europe 22.9 GW of new PV capacity were added comparative to the previous year. In Figure 2.3 is represented the evolution of the installed solar energy capacity around the world, where it is possible to see the explosion of installed solar capacity in the beginning of the last decade [11].

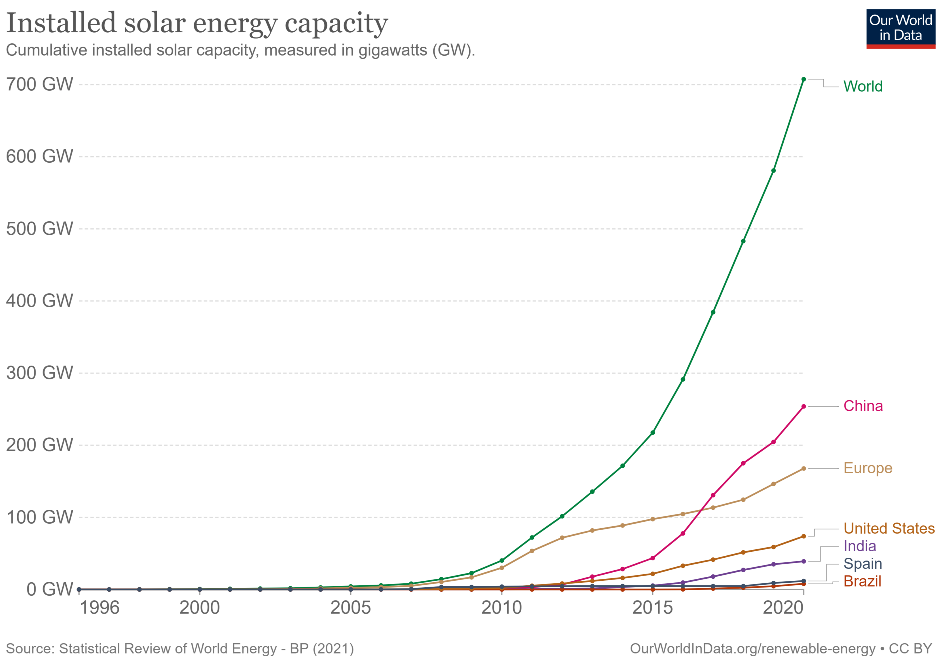

Figure 2.3: Installed solar energy capacity in GW [11].

Solar energy maintain the title of the most attractive power generation source, as it is possible to see in Figure 2.4 where the solar have the largest growth comparative with the others renewable energy resources in the last decade. In 2020 the installed capacity of solar energy is 2000 % more comparative to 2010 which is a larger growth than all others renewables together.

Companies from United States, Germany , Japan and South Korea dominated the core technology of poly crystalline production. However, since 2005, poly crystalline industry in China start to take a dominant position in the world PV industry mainly because of the rapid developments promoted of its PV industry technology promoted a lower cost of their PV technologies [40].

Nowadays, the variety of materials available in the market to use to make solar cells is huge. However, the market has been lead by silicon-based solar cells, mainly because of their high efficiency and low cost.

Another solution that has been implemented on a large scale, but not as much as the silicon-based solution is thin film technology. This technology have a lot of potential because of it high flexibility in nature and low cost. Although, the conversion rate of this technology is still causing some concerns [41]. In Figure 2.5, is possible to see the main materials used in the manufacturing of solar cells.

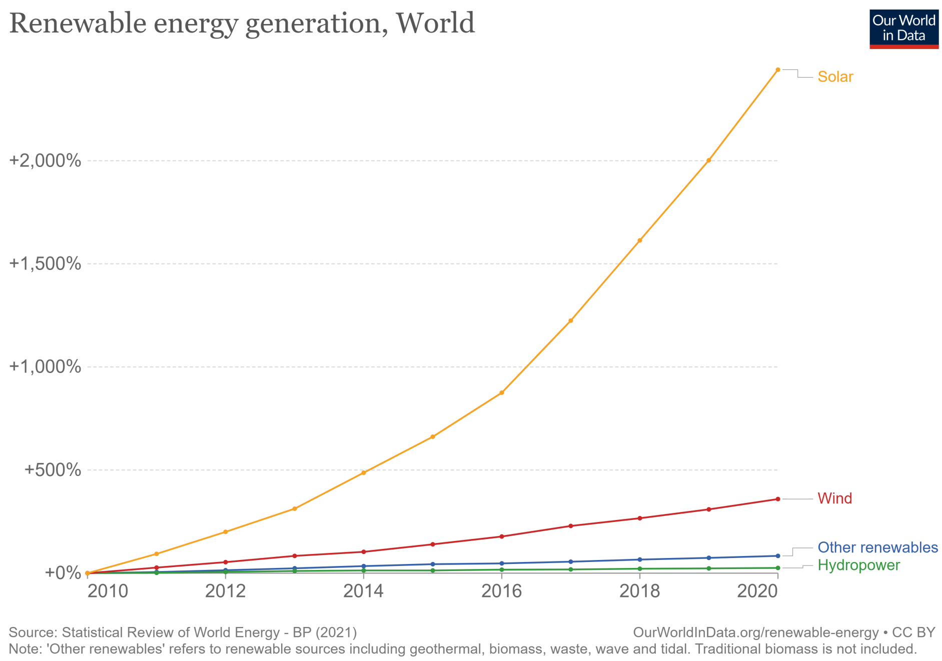

Figure 2.4: Renewable energy generation growth between year 2010 and year 2020 [11].

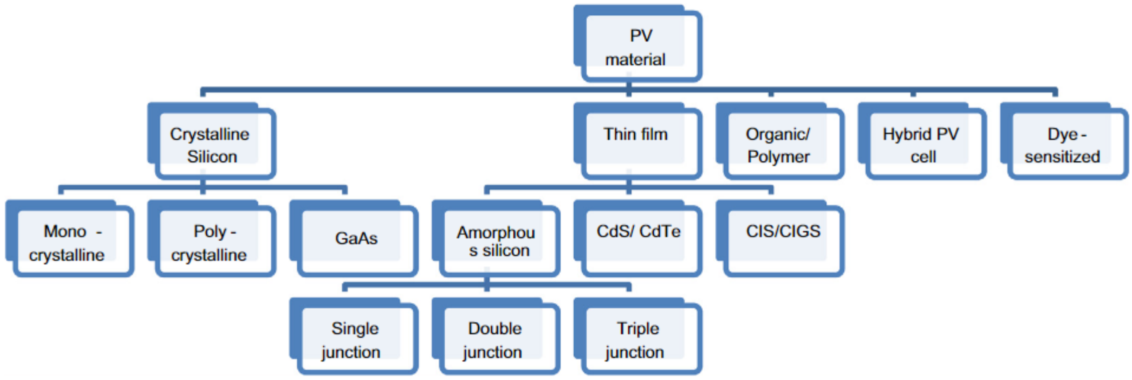

Figure 2.5: Materials used in solar PV cells [41].

- **Crystalline silicon solar cells**

  The main benefit of using this material is the high efficiency compared to other solutions and the easy availability that has compelled manufacturers to use it as a material for solar cells. Mono-crystalline silicon cells are used in most cases due to their high efficiency. Although, the high manufacturing cost is a concern for manufacturers and end users consumers. An alternative is poly-crystalline solar cell, which has lower cost compared to mono-crystalline.

  Another solution is the GaAs based solar cell, it is a semiconductor, composed of Gallium (Ga) and Arsenic (Ar), which have a structure similar to silicon. This solution has high efficiency and low weight, but has the disadvantage of high cost compared to both silicon solutions. One of the notable advantages of the latter solution is the high thermal resistance that makes it suitable for concentrated photovoltaic module for power generation, hybrid use and space applications [41].

- **Thin film solar cells**

  Thin film solar cells are cheaper when compared to silicon-based solar cells, resulted from the less material needed for the manufacturing process. Amorphous silicon is non-crystalline, has a form of disordered silicon structure, giving rise to higher light absorption rate values compared to mono-crystalline silicon [41].

  Therefore, this solution is more widely used compared to CIS/CIGS (Copper Indium Selenide / Copper Indium Selenide) and CdS/CdTe (Cadmium Tellurium). Because of the strong light absorption comparing with silicon, these are thin-film solar cells because thin layers of these materials can be deposited onto substrate materials such as glass or plastic.

2.3.2 PV systems technology applications

- **PV system integrated in the grid**

  Integrating photovoltaics into electricity grids is a great solution to reduce losses in transmission and distribution cables, to increase resilience in the grid, to lower the costs of power generation and to reduce the need to invest in new utility to increase the generation capacity of the grid [42]. These PV systems, can be integrated as a mounted or rooftop mounted application or building integrated PV (BIPV) system which can include thermal generation (BIPV/T), which produces electricity energy to use directly in the grid or to store in ESS for further use.

- **Building integrated PV/Thermal systems**

  PV/T systems combine photovoltaic solar cells with a solar thermal collector. This system has both capabilities of converting incident radiation into electricity and heat, transfers the waste heat from the PV module to a heat transfer fluid which can be air or water, increasing the efficiency of the system compared to both systems individually.

  In order to improve the electrical and thermal performance of a building PV/T is a great solution, in these technologies, the exhausted fluid is used for crop drying or surface heating in buildings [43]. A common use of this application is to build it integrated in the building. This consists in the integration of PV systems or PV/T systems in the walls or facades of the buildings, which the panel is installed with an air gap or as a part of the building, as it is shown in Figure 2.6.

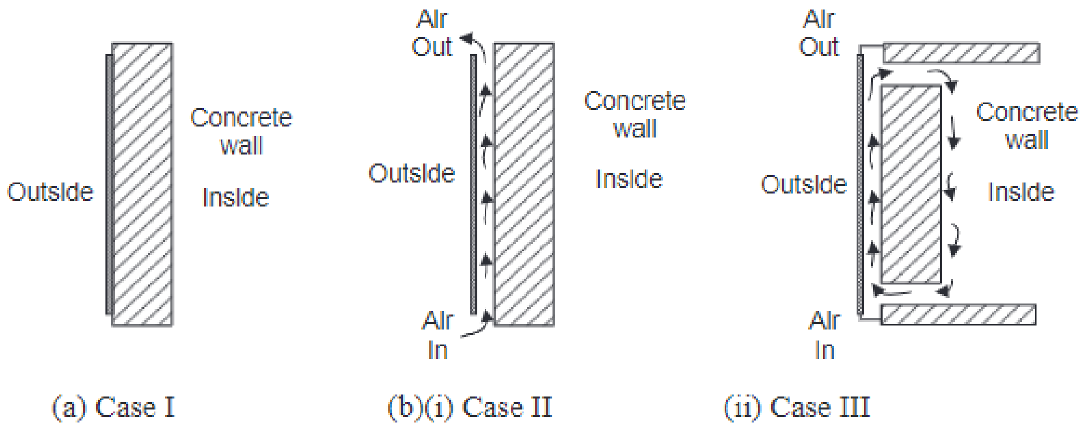

Figure 2.6: (a) Building integrated PV system attached to the building wall without ventilation gap, (b)(i) building integrated PV attached as facade with air gap and (b)(ii) building integrated PV/T system attached as a ventilated facade with indoor airflow used to cool the PV panel [43].

- **Underwater PV systems**

  This application is in a state of research but is paving the way for a new area of application for PV systems, as can be seen in reference [44]. Supported with the latest technology, this research could solve some challenges that long term power sources in marine electronics, marine corporations and others operations underwater power systems impose. Most of these systems are powered by conventional batteries so, using solar photovoltaic cells the systems can increase their reliability, providing cooling, cleaning, and avoiding challenges due to land based constraints.

2.3.3 Solar PV Output Power

The output power in a PV cell is affected by the solar irradiance received and the ambient temperature. To demonstrate the calculation of this output power, is considered an electric equivalent circuit from a single diode PV cell with a resistance in series that is from reference [45]. From that equivalent circuit is possible to calculate the available power to be dispatched from the PV cell $P_{av.c}(t)$ with Equation 2.1.

$$P_{av.c}(t) = FF(t).V_{oc}(t).I_{sc}(t) \tag{2.1}$$

Where $FF(t)$ is the PV cell fill factor, $V_{oc}(t)$ is the open circuit voltage and $I_{sc}(t)$ is the short circuit current of the pv cell that are calculated using the Equations 2.2 and 2.3.

$$V_{oc}(t) = V_{oc.std} + K_v(T_c(t) - 25) \tag{2.2}$$

$$I_{sc}(t) = (I_{sc.std} + K_i(T_c(t) - 25)).\frac{G_T(t)}{1000} \tag{2.3}$$

Where $V_{oc.std}$ and $I_{sc.std}$ are the open circuit voltage and short circuit current for standard test conditions with, K_v and K_i, that are the related coefficients, of the PV cell.

The PV cell temperature $T_c(t)$ is affected by the solar irradiance $G_T(t)$ and by the measured ambient temperature $T_a(t)$ so in Equation 2.4 is shown how to calculate the temperature in the PV cell.

$$T_c(t) = T_a(t).\frac{NOCT - 20}{800}.G_T(t) \tag{2.4}$$

Where $G_T(t)$ is the total irradiance, which results from the summary of the direct beam irradiance ($G_B(t,\beta)$), the diffused irradiance ($G_D(t,\beta)$) and the reflected irradiance ($G_R(t,\beta)$), represented in Equation 2.5 where β is the PV panel tilting angle. The $NOCT$ is the Nominal Operating Cell Temperature which is stipulated by the panel characteristics.

$$G_T(t) = G_B(t,\beta) + G_D(t,\beta) + G_R(t,\beta) \tag{2.5}$$

The total PV power generation of a panel depends on the number of panels connected in series N_s and in parallel N_p. So the total generated power from the PV array $P_{av.pv}$ can be calculated using Equation 2.6, where N_c is the total number of PV cells of each panel.

$$P_{av.pv}(t) = P_{av.c}(t).N_c.N_s.N_p \tag{2.6}$$

2.4 Energy Storage Systems

ESS technology evolution led to an evolution of the battery storage along with other energy storage types but ultimately with a different direction of peak shaving or short term outage prevention. Nowadays, energy storage systems leads to delay capacity [46], network expansions [47], frequency regulation [48], voltage balancing [49], etc. Energy storage technology is usually categorized based on their application time scale, such as instantaneous when it is applied for less than a few seconds, for less than a few minutes is considered short term application, for less than a few hours it is mid term and for less than a few day it is long term, these terms are referring to the time that it takes between the storage and the use of the energy [50].

The interest in electricity storage increased exponentially with the rise of variable renewable power sources penetration in the grid, especially photovoltaic and wind power that emerged from a few kW to hundreds of MW. These power sources, as a result of their volatility resulted from the uncertainty of weather and seasonal fluctuations, have an uncertainty output so, storage is used to balance the loads resulting in a decrease of losses and an increase of the system reliability and efficiency [51, 52].

There are a large diversity of types of batteries in the market such as, lead acid, lithium ion, sodium sulfur, etc. each one have different characteristics that make each of them suitable for different objectives. These battery specifications that are referring to each type of battery are energy capacity cost, dept of discharge, efficiency of charge and discharge, life cycle, discharge duration, power density, environmental impact, etc. [53] [54]. The battery selection is linked with many parameters, as the application objective, position in the grid, geographic location, etc. In reference [55] was made a study for the household-level battery preferences for consumers.

The improvement of quantum in terms of cost, reliability and efficiency, resulted in a development of the manufacturing industry, opening a path for a new electric storage revolution increased by the cost efficiency of lithium-ion batteries. This fact is bringing new opportunities for distributed generation of solar energy. For grid connected microgrids, PV-battery systems could provide, a more efficient reduce of the peak of consumption of a household and lower the total cost of daily energy in order to benefit the consumer [56]. For off-grid this solution will provide for the poor regions, new opportunities in terms of electricity access.

There are a lot of different technologies for an electrical energy storage system such as, flywheel energy storage (FES), battery energy storage system (BESS) and hydrogen based energy storage (HES). Inside the BESS field there are a lot of different technologies such as, lead acid battery, lithium-ion battery, sodium-sulfur battery, etc.

FES technology consists in a mass that is rotating on two magnetic bearings with the objective to reduce the friction, by accelerating the flywheel, the system is working as a motor so the load that it is linked charge the flywheel with energy then if the flywheel reduce it speed, the flywheel is discharging energy to the load [57].

A battery is considered an electrochemical device that by electrochemical reactions is capable to supply electric energy from the stored chemical energy. The lead-acid battery, is the cheapest and most mature BESS technology. This batteries are based on chemical reaction using lead dioxide to form the cathode electrode, lead, to form the anode electrode, and sulfuric acid that constitutes the electrolyte. The main disadvantages of these batteries are the poor efficiency at high and low ambient temperatures and also their short lifetime relative to other technologies [57].

The sodium-sulfur battery surges with the objective to achieve higher power and energy density. This battery consists in a positive electrode with liquid sulfur and as a negative electrode liquid sodium separated by a solid alumina ceramic electrolyte. This type of battery seems to be much more attractive in terms of energy density and has a long cycle capability which is beneficial for power regulation in microgrids [57].

For small applications, lithium-based batteries are the chosen technology. Besides that there are companies which are developing lithium-ion batteries for high energy configurations such as electric vehicles. The lithium-ion cells have a high power density makes that this battery could be applied to a wide range of applications [57].

2.5 Demand Response Programs

In electrical power systems are faced various obstacles, such as, low efficiency, reliability problems, energy losses, high pollutant gases emissions, high possibility of market power exercise, etc. With the traditional electricity tariffs, the consumer does not have incentives to adjust their usage according to supply costs because, the wholesale electricity market price is not directly linked with the retail price tariffs leading to an inefficient usage of resources from the consumers. The electricity price even if the consumer regulate their own demand under the flexibility limits, using the traditional flat tariff method, the price does not change in order to compensate the load reschedule of the consumer.

Because of this approach, during peak hours of consume or contingencies, the demand will be extremely high, having in some cases the need to do investments in the grid or production in order to the system be able to support that situations. Resulting in an increase of the electricity supply cost.

Demand Response (DR) programs are a very efficient strategy to solve the mentioned challenges. DR is defined as "changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized" [58]. Thus, DR programs incentive the consumers to reschedule their demand pattern in order to help the power system to supply more efficiently all the costumers in peak hours or in contingencies. It is considered as the most cost effective and reliable solution for the reduction of demand at peak periods.

Due to the benefits of DR this could improve the reliability and efficiency of electricity markets, being a key element for the growth of smart grid [59]. DR is also know as a powerful proceeding to facilitate the integration on the grid of RES like wind and solar [60], an useful method to encourage consumers to increase their consumption at off peak periods and decrease their load profile when the power generation output is low.

DR programs can be divided in two different categories, the first one are incentive based DR programs which, award the consumers for changing the consumption pattern in order to low the peak demand, with incentives. The second one are price-based DR programs, where the consumers are charged with different rates at different consumption times so, the cost of electricity supply affects the retail tariff. In Figure 2.7, is possible to see both of the two different categories and all programs associated to each one of them.

2.5.1 Price-based DR programs

Using variable energy usage tariffs, with the objective to optimize the power system operation, price-based DR (PBDR) programs are used to shift a percentage of consumption from the on peak periods to off peak periods of demand. The mainly used PBDR programs are time-of-use (TOU), critical peak pricing (CPP) and real-time pricing (RTP).

- **Time-of-use (TOU) program**

  TOU electricity pricing is widespread in developed countries. This scheme of pricing have benefits in reducing the generation and transmission costs, significantly peak reduction [61], reduction of consumers electricity tariffs [62], reduction of the wholesale market prices [63], improving fairness in retail pricing [64] and facilitating the deployment of distributed generation including RES, assuming to be an environmental benefit [65].

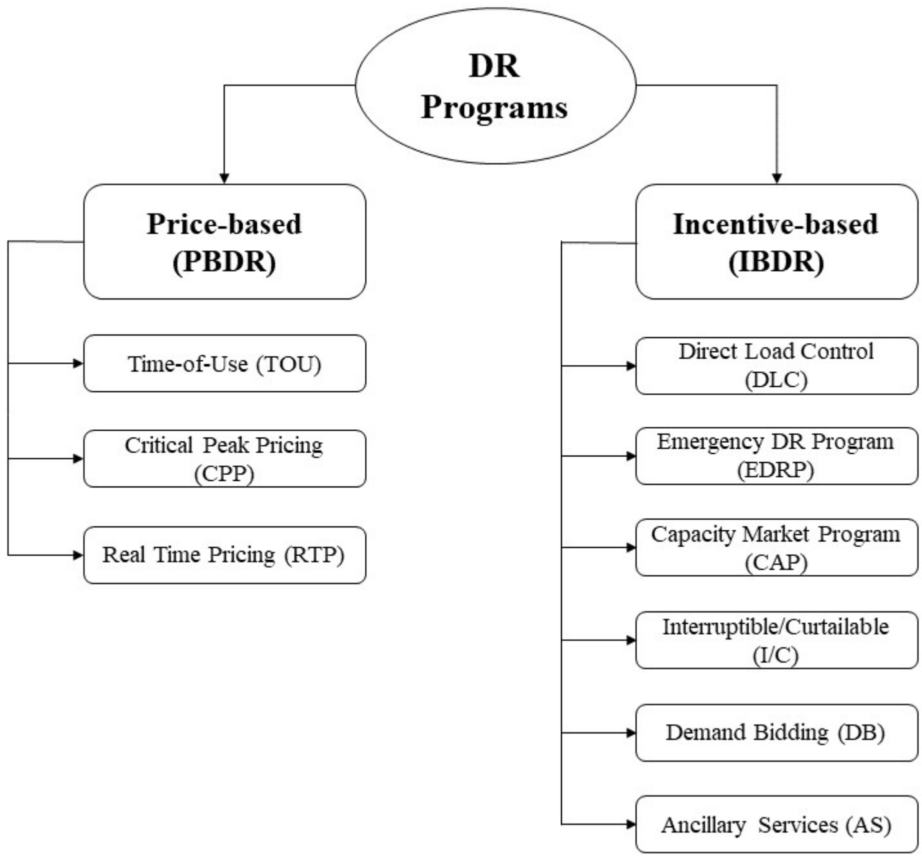

Figure 2.7: Different types of Demand Response Programs (DRP).

TOU program users, consume energy in different time intervals of the day that are charged at different prices so, it uses elasticity matrix to model their programs knowing that the elasticity of each user is unique in most of the cases. If it is considered two time blocks such as, on peak or off peak, the electricity price at the on peak block will be much higher than the off peak block so, the users are induced to shift their loads to the off peak in order to reduce the system congestion. [66], in Figure 2.8 is an example of a TOU electricity tariff.

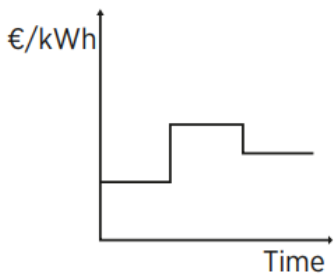

Figure 2.8: Example of a TOU electricity tariff [67].

- **Real time pricing (RTP) program**

  The tariffs resulted from RTP program are composed by the wholesale price of electricity with a the supplier margin for their work in deliver energy. The price is determined based on short periods of metering of consumption that could be from one hour or 15 minutes [68]. To increase the adoption of these programs smart meters associated with communication and information technologies are essential. RTP prices vary during the day which not happens with the TOU or CPP programs. In Figure 2.9 is represented an example of a RTP electricity tariff.

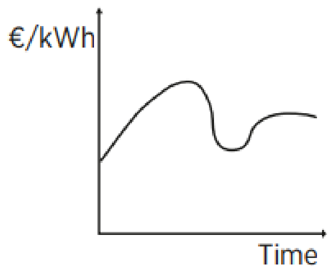

Figure 2.9: Example of a RTP electricity tariff [67].

- **Critical peak pricing (CPP) program**

  In CPP programs, are established contracts for one year, with a fixed price of electricity, but with an stipulated number of days which will have a considerably rise in the electricity price. In Figure 2.10 is possible to see an example of a CPP electricity tariff. This program is an mix of static and dynamic nature of pricing, naturally this program is a static one but some days of the year, under specific trigger conditions, such as reliability problems of the system or extremely high supply prices, it turns into a dynamic pricing program [69].

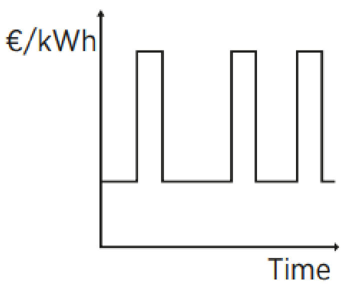

Figure 2.10: Example of a CPP electricity tariff [67].

2.5.2 Incentive-Based DR Programs

Incentive-based DR (IBDR) programs offers financial rewards to their users if they are able to curtail or reduce their energy consumption. Through that, IBDR programs motivates the participation of consumers in their programs in order to reduce the on peak demand compensating that reduction in the off peak period. There are different types of IBDR programs, such as direct load control, load curtailment service, demand bidding, ancilliary services, capacity market program and emergency demand reduction all of them with the objective to increase the demand flexibility of the system [70].

Incentive-based DR programs have the objective to lower or curtail consumption by offering rewards (often financial) to the consumers that participate in it. The main goal of DR programs is to influence the consumer's energy profile and incentives them to participate in such programs. Implementation of DR programs reduces the energy consumption during peak periods while increasing the amount of energy usage during the off-peak periods. There are different types of incentive-based DR programs including, direct load control, load curtailment service, demand bidding, ancillary service program, capacity market program and emergency demand reduction.

These programs can be classified as voluntary, where the consumers are not penalized if they do not reduce their consumption and they are rewarded if they do it. Mandatory, where The enrolled consumers are subject to penalties if they do not respect the curtailment or reduction of load when the program asks for it, and also market clearing, more used with larger consumers that are motivated to offer or to provide load reductions at a price that they are willing to be curtailed or to identify how much load they would be willing to curtail at posted prices.

- **Direct Load Control**

  In direct load control programs, a utility or system operator, remotely shuts down or reduce the consumption of the consumer electrical equipment in order to control their consumption in situations of reliability contingencies in exchange of financial rewards or bill credit. The operation of these programs occurs at peak demand periods. Although, this is operated with the objective to achieve an optimal solution which needs to be economically profitable for the consumer and for the system, avoiding purchases of electricity at high on peak prices [71]. These programs are classified as voluntary.

- **Interruptible/curtailable service**

  Interruptible or curtailable service consists in contracts that are made with the user which in exchange for reducing their consumption during system contingencies, they receive a discount rate or bill credit. If the consumers do not curtail or reduce their consumption when it is needed they will be penalized. These tariffs are always offered as a service included in an electric utility or load serving entity as a DR aggregator [72].These programs are classified as mandatory.

- **Emergency Demand Response Program**

  Emergency demand response programs provides an incentive payment to consumer for reducing their consumption during situations which the reliability of the system is in danger. Customers, if they want, could not curtail when notified and because of that they just do not receive the reward. The amount of payment is specified beforehand [73]. These programs are classified as voluntary.

- **Capacity Market Program**

  In capacity market programs, consumers have defined reductions of load when system contingencies appears and are subject to a penalty fee if they do not respect the stipulated load reduction. Customers receive guaranteed payments even if the load curtailment is not called [74]. These programs are classified as mandatory

- **Ancillary Service Markets**

  In ancillary services markets consumers are allowed to bid load curtailments in ISO markets as reserves. If their bids are accepted, they are paid at the market price just for being able to reduce their loads in situations that it is needed. Customer needs to have the capacity to quickly adjust their load to be able to participate in these markets [75].

- **Demand Bidding**

  In demand bidding programs, the consumers can propose the quantity of load that they are capable to reduce at the posted price or can offer a reduce quantity at a price that they would want to curtail consumption. If customers proposes are cheaper than alternative supply bids, load curtailments are dispatched and customers are obligated to curtail their load. If the consumer reduce their load when the wholesale prices are high, their rewards increase but the rates to participate in this market are fixed [76].

2.5.3 DR Aggregator

The aggregation of DR programs is essential for the future smart grids, in order to enrolled the individual consumer in the electricity markets. DR aggregators have the goal to trade large volumes of DR that comes from different DR programs with different types of consumers in order to promote their participation in DR programs. Thus, is it a crucial step to increase the needed flexibility of demand in the power system.

DR aggregator can work as an interface between the electricity consumers and the independent market operator (ISO), optimizing the demand and supply schedules in order to increase the balance between them. DR aggregator acts like a third-part and intermediate the power market participants that are considered the purchasers with the end user consumers, who make DR programs contracts with the DR aggregator in order to sell their DR.

Aggregators realize that end-users consumers are able to provide system capacity, flexibility of their load and power generations during critical times such as peak periods or contingencies. Engaging various end users consumers, the DR aggregator become able to participate in the wholesale energy market if their accumulative capacity is large enough.

Using DR aggregators, it is now possible to integrate in the energy market consumers that as a single identity doesn't had the minimum requirements to enter in it. This turns the market more fair for the consumers once they are participating in it.

With all the investments that are being made in information communication technologies (ICT) [77] and in advanced metering infrastructures (AMI) [78], the integration of DR aggregators in the power system become more easy. These two areas of investments are essential for the smart grid structure and motivates the participation of the consumers in electricity markets shifting the role of consumers to an active part of the system.

There are some different types of aggregator that instead of aggregating DR, are used to agregate DERs or EVs with the objective to increase the active role of all participants creating a decentralized power system [79]. With the use of batteries and local generation, it is possible to overcome the challenges that are presented from the impact that RER introduce in the power system. The aggregation of the participants of the system through different strategics is essential to increase the impact that the user have on the energy market electricity prices. It is possible too, to aggregate V2G systems with DR programs [80], in order to use their available power and storage system.

2.6 Robust Optimization Method

In most of programming linear models, it is necessary to consider uncertainty in data related to demand, costs, weights, etc. Most practical problems have uncertainty in their data. Soyster, in 1973, was one of the first to discuss problems with uncertainty in the constraint data. Soyster believed that the nominal data in the technology matrix can vary over a range of coverage, but this random data always assumes the worst case, undermining the optimal value of the nominal problem.

There are less conservative approaches compared to Soyster's. Ben-Tal and Nemirovski, in 2000, proposed models in which the uncertain data is perturbed by a random variable. With this, they tried to analyze if these data are influenced by this perturbation. In addition, in 2004, Bertsimas and Sim worked on the hypothesis that not all data assume the worst case, respecting the constraint violation guarantee.

Bertsimas and Sim method introduced a budget uncertainty parameter (Γ), not necessarily classified as an integer. This uncertainty budget takes values from 0 to the number of uncertain parameters, and it is essential to control the level of conservatism. Adjusting Γ it's possible to control the level of conservatism of the solution, where for 0 the uncertainty is not taking into account and for the maximum value of Γ, uncertainty is considered for all the parameters possible, that we are studying [81].

The objective of the RO method is to obtain a feasible solution for any scenario of the uncertain parameters and a solution that is optimal for the worst case scenario of the uncertain parameter. To solve the problem, the RO method just needs the average and upper and lower limits of the uncertain parameter. The solution provided by the RO programming method is optimal for all realizations of the uncertain parameter because, in the decision making process is considered the worst case scenario [82, 83].

A generic model that could be applied to a linear programming problem for the robust optimization approach is presented in the next equations in order to better understand the purpose and functionality of the programming method. Considering a minimization problem in Equation 2.7.

$$Minimize \qquad \sum_i f(x_i) + \sum_j e_j.x_j \tag{2.7}$$

$$Subject\ to \qquad g_1(x) < 0,\ g_2(x) = 0;\ x \in x_i, x_j \tag{2.8}$$

Where x_i stands for the vectors of i^{th} continuous decision variable and x_j stands for the j^{th} binary decision variable. e_j is the coefficient of the variable x_j in the objective function and is assumed as an unknown parameter, which is just known it lower and upper bounds so, it could range from e_j^{min} to $e^m ax_j$. $g_1(x) < 0$ and $g_2(x) = 0$ are the inequality and equality constraints of the model. Therefore, the robust optimization can be formulated as Equation 2.9.

$$Min\{\sum_i f(x_i) + \sum_j e_j^{min}.x_j + Max_{\{j||j|\leq\Gamma\}}\ \{\sum_j (e_j^{max} - e_j^{min}).x_j\}\} \tag{2.9}$$

The max term in Equation 2.9, is considered for all uncertainty parameters that not exceed Γ. The interval of e_j could be found from the forecasting model if it provides this values. If not, e_j interval may be considered as a percentage of forecast value around such forecasted value.

Hence, it can be considered a vulue α, wich corresponds to the percentage from the forecasted value which the upper bound e_j^{max} and lower bound e_j^{min} will have, so the forecasted value should be multiplied by $(1 \pm \alpha)$. This α value should range from 0 to 1 in order to adjust the level of uncertainty that is taking in consideration.

The Γ corresponds to the level of conservatism of the optimal solution and is defined as an integer parameter. It takes values in $[0, N_J]$, where N_J is the number of uncertain parameters. If Γ is set at zero, it means that the RO program is ignoring the effect of uncertainty in the model, which is the same to solve the deterministic problem. If $\Gamma = N_J$, it means that uncertainty is considered for all slots of the uncertainty parameter, so that means that this is the most conservative case of the RO approach. To deal with the optimization complexity of Equation 2.9, are considered two auxiliary variables X and y_j converting Equation 2.9 into Equation 2.10.

$$Min\ \{\sum_i f(x_i) + \sum_j e_j^{min}.x_j + Max_{\{\sum_j \leq \Gamma, 0 \leq X \leq 1, x_{jj}\}}\ \{\sum_j (e_j^{max} - e_j^{min}).y_j.X\}\} \tag{2.10}$$

Furthermore, by using the duality theory, converting the min max problem to a full minimization problem as it is shown in Equations 2.11 to 2.16.

$$Min\ \{\sum_i f(x_i) + \sum_j e_j^{min}.x_j + z.\Gamma + \sum_j \xi_j\} \tag{2.11}$$

$$z + \xi_j \geq (e_j^{max} - e_j^{min}).y_j \quad j = 1, 2, ..., N_J \tag{2.12}$$

$$\xi_j \geq 0 \quad j = 1, 2, ..., N_J \tag{2.13}$$

$$y_j \geq 0 \quad j = 1, 2, ..., N_J \tag{2.14}$$

$$z \geq 0 \tag{2.15}$$

$$x_j \leq y_j \quad j = 1, 2, ..., N_J \tag{2.16}$$

If is it considered a maximization problem, in Equation 2.11, instead of the maximization of the range interval, it is minimized. Then, using again the duality theory the max min problem transforms only on a max problem.

2.7 Novel Approaches

In this section, will be referenced some approaches from others works in the recent year, similar to the developed work in this thesis, in order to compare and set the similarities and differences with this work.

Thus, In reference [84], is presented an optimization model to determine the optimal operation of a DR aggregator, which is compound by a portfolio of different DR programs in wholesale electricity markets. This DR aggregator consider a strategic participation in the real-time market and the DR programs portfolio is composed of contracts of load curtailment and flexible loads. The proposed model in this reference is a stochastic bi-level program in order to lead with the market prices uncertainty and is solved using mixed-integer linear programming (MILP).

In reference [85], is presented a model for a aggregator that manages a set of resources such as PV, batteries and thermal energy storage using electric water heaters. The resources are managed in order to participate in the day-ahead energy and local markets using a model of MILP problem with the objective to minimize the day ahead operation cost. In this model is considered uncertainty of the electricity prices, PV production and load using a RO to include these three uncertainties.

A stochastic optimisation programming for scheduling a microgrid is considered in reference [86]. In this model is considered the uncertainty of renewables resources and the participation of the EVs owners in the parking lot. There are considered heat and power generation, thermal energy storage, and auxiliary boilers and also, PBDR and IBDR programs are integrated in the multi-energy microgrid to manage a commercial complex.

The interaction between the electricity market and the end users is achieved using a DR aggregator to handle and manage uncertain parameters and reduce the impact of them in the aggregator operation is approached in reference [70]. In this paper, is proposed a model that deals with the uncertainty of the wholesale market prices and the participation rate of consumers in the engagement of DR programs, using a hybrid Stochastic-Robust optimization program. In this model is considered two DR programs, TOU and IBDR and are applied to residential, industrial and commercial consumers. In addiction, an ESS is assumed to be operating together with the aggregator. The proposed MILP hybrid stochastic-robust model improves the evaluation of DR aggregator's scheduling for the probable worst case scenario.

In reference [87], is based on a game theory approach to obtain the best bidding strategy for DR aggregators in electricity markets. It is applied a RO method to handle with energy price uncertainty.

A DR aggregator to purchase energy from short term electricity market integrated with wind generation is proposed in reference [88]. To obtain the optimal decision making of the DR aggregator is used a regret-based stochastic bi-level framework aiming to maximize its expected profit in a competitive market considering the uncertainty and volatility of wind energy prices.

In this reference [89], is considered a DER aggregator who manages wind turbines, solar PV systems and battery energy storage units and also, implements a RTP demand response program. The DER aggregator is able to bid in the electricity market in order to procure electricity and schedule its DER generation to balance demand and supply. In this model is considered uncertainty from renewable generations and from the responsiveness of the customer to the aggregator's profit, using a RO programming method with day-ahead optimal bidding and schedule model of the DER output and battery units.

Chapter 3

Model Formulation

3.1 Design of the Model

The model developed in this thesis is composed by 3 different types of electricity consumers, which are residential, commercial and industrial. Each one of the consumers type is linked to the electricity market using a DR aggregator, which aggregates all consumers demand in order to sell it to the ISO.

The consumers can establish contracts with the DR aggregator using two different types of DR programs, such as, reward-based DR programs that are an IBDR program type or TOU programs that are PBDR program type.

Then, the obtained DR aggregated is exchanged with purchasers through the establishment of DR option agreements or fixed DR contracts. In addition, is integrated closer to the consumers solar PV generation for self-consumption and an BESS that may be charged with the excess of PV generation and discharged when the prices of energy are higher and the PV generation is not enough to supply all demand.

The BESS could also be charged directly with the power bought by consumers to DR aggregator, when the prices of electricity are lower. All this functionalities have as a purpose to maximize the DR aggregator profit and also incentive the participation of consumers giving to them an active role on the power system.

In Figure 3.1, is schematized the behavior and power exchanges for all the system that was modeled. Considering in the bottom block the three consumer types equipped with solar PV generation and BESS. Then these consumers are aggregated by the DR aggregator using the two types of DR programs, TOU and reward-based DR. Finally, through fixed DR contracts and DR option agreements the DR aggregator link the consumers to the power system.

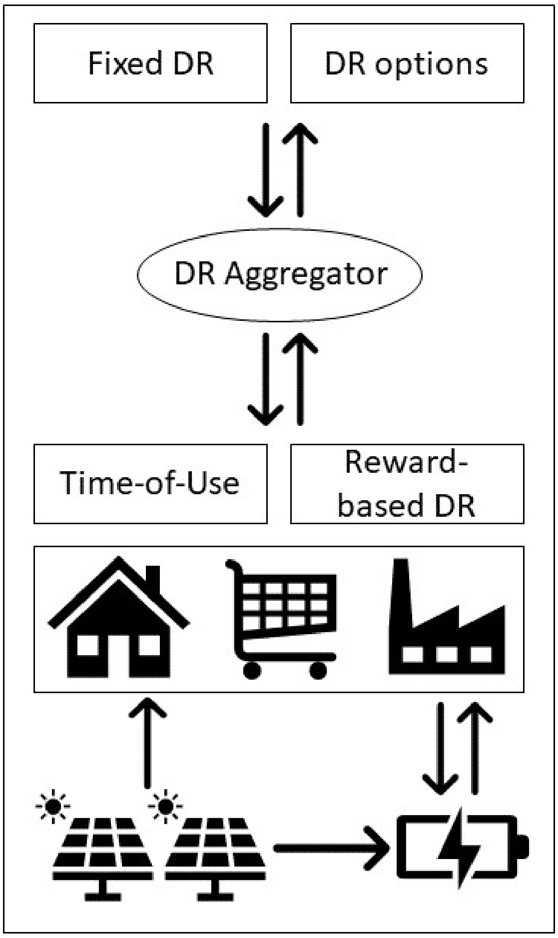

Figure 3.1: DR aggregator structure with PV generation and BESS system

Such arrangement is used in order to motivate the consumers to increase their consumption at off peak periods, and at on peak periods DR is obtained from consumers, which means that they reduce their consumption and with the introduction of the PV generation and BESS in the consumer side, they could decrease the need to purchase electricity from the aggregator using directly the PV electrical generation and if it isn't enough, the BESS at each time slot.

This code was constructed based from the model for DR aggregator presented [90]. The main contribute of this thesis is to add the solar PV generation to the consumers and an electrical energy storage system, in order to analyse the impacts that it have on the DR aggregator profit and the interactions between all the DER that are integrated in this model, PV generation, BESS, DR programs. Firstly, it is analyzed the behaviour of the deterministic optimization model, in order to see the impact of the integration of PV generation and battery, on DR aggregator functionality. Finally is inserted the uncertainty of PV generation in order to simulate it uncertain nature, using a robust optimization programming method.

3.2 Mathematical Formulation

3.2.1 Fixed DR Contracts

The acquired demand response by the aggregator is traded to the purchaser using block b of f^{th} contract including the the prices including ($\lambda_{f,b}^{DR}$) and DR ($P_{f,b}^{DR}$), that is expressed by Equations 3.1 and 3.2. The $P(FDR)$ corresponds to the income in dollars for the DR aggregator, resulted from the sale of DR to purchasers that was bought and to the consumers using DR programs and then aggregated. N_b and N_f are the number of available blocks and contracts respectively.

$$P(FDR) = \sum_{t=1}^{T} \sum_{f=1}^{N_f} \sum_{b=1}^{N_b} P_{f,b}^{DR}(t).\lambda_{f,b}^{DR}(t) \tag{3.1}$$

$$P_{f,b}^{DR,min} \leq P_{f,b}^{DR}(t) \leq P_{f,b}^{DR,max}, \quad \forall t \tag{3.2}$$

3.2.2 DR Option Agreement

After examining the profitability of the DR option chosen for the day, the DR aggregator set an aggrement with the purchaser. This agreement can be cancelled but the DR aggregator needs to pay a penalty fee to the purchaser. This agreement is expressed in Equation 3.3. Where, the first term refers to the income for DR aggregator resulted from the purchase of a DR specified in the pool of the day at the option chosen by DR aggregator at every hour $P_{op}^{DR}(t)$, at the correspondent price $\lambda_{op}^{DR}(t)$ specified in the pool of options.

The second term is related to the penalty that the DR aggregator have to pay to the purchaser if it cancel the agreement, to see if the agreement is executed or cancelled at every hour of the day is used the binary variable $v_{op}^{DR}(t)$, which is 0 if the agreement is cancelled or 1 if it is executed. Equation 3.4 is a constraint used to limit the value of agreed DR in the DR option agreement.

$$P(ODR) = \sum_{t=1}^{T} \sum_{op=1}^{N_{op}} [P_{op}^{DR}(t).\lambda_{op}^{DR}(t) - (1 - v_{op}^{DR}(t)).f_{op}^{pen}(t)] \tag{3.3}$$

$$P_{op}^{DR,min} \leq P_{op}^{DR}(t) \leq P_{op}^{DR,max}, \quad \forall op = 1,2,...,N_{op} \tag{3.4}$$

3.2.3 Reward-based DR program

This program is modeled, using Equations 3.5 to 3.9. With Equation 3.5 it is possible to model the reduction of load by the consumers in which $PF(t)$ indicates the participation level of consumers from 0 (unattainable) to 1 (attainable). Equation 3.6 refers to the donated reward to the consumer for the chosen block at each hour, which is limited by Equation 3.7. the Equation 3.8 and 3.9 certify that the model only chose one reward-based DR step for the load reduction at each hour of the day.

$$P^{DR}(t) = \sum_{j=1}^{N_j} PF(t).\overline{P}_j^{DR}(t).v_j^{DR}(t), \quad \forall t, \forall j \tag{3.5}$$

$$R^{DR}(t) = \sum_{j=1}^{N_j} R_j^{DR}(t), \quad \forall t, \forall j \tag{3.6}$$

$$\overline{R}_{j-1}^{DR}(t).v_j^{DR}(t) \leq R_j^{DR}(t) \leq \overline{R}_j^{DR}(t).v_j^{DR}(t), \quad \forall t, \forall j \tag{3.7}$$

$$\sum_{j=1}^{N_j} v_j^{DR}(t) = 1, \quad \forall t, \forall j \tag{3.8}$$

$$v_j^{DR}(t) \in \{0,1\} \tag{3.9}$$

3.2.4 Time-of-Use program

In TOU programs, the DR aggregator offers different prices to the consumers in order to possibility the consumer to modify their electricity usage profile according to the offered prices. Elasticity of consumers electricity consumption and, their participation in TOU program are proportional with each other, which means that if the price decrease, more flexible should be the consumer. This programs is modeled by Equation 3.10. The $TOU(t)$ is related to the bill difference resulted from shifting loads by the consumer, which $E(c,t,p)$, refers to the elasticity of the consumer.

$$TOU(t) = \sum_{c=1}^{N} D_0(c,t) \sum_{p=1}^{P} E(c,t,p).\frac{\lambda(c,p) - \lambda_0(c,p)}{\lambda_0(c,p)}, \quad \forall t \tag{3.10}$$

3.2.5 Battery Energy Storage System

For the electrical energy storage system constraints, the Equations 3.11 and 3.12, respects to the limitation of the power discharged from the battery and the power charged to the battery at each hour of the day, respectively. In Equations 3.13 to 3.16 is defined the SOC constraints with 3.13 and 3.14 defining the initial state of charge of the battery. Equations 3.15 and 3.16, respects to the SOC of the battery in the next time slot before one hour charging or discharging, and the SOC value upper and lower limitation, respectively.

$$0 \leq P_{dch}(t) \leq u_{dch}(t) + P_{dch}^{max}, \forall t \tag{3.11}$$

$$0 \leq P_{ch}(t) \leq u_{ch}(t) + P_{ch}^{max}, \forall t \tag{3.12}$$

$$a.SOC^{max} = SOC(t = T_{final}) \tag{3.13}$$

$$SOC^{initial} = a.SOC^{max} \tag{3.14}$$

$$SOC(t) = SOC(t-1) + P_{ch}(t).\eta^{ch} - \frac{P_{dch}}{\eta^{dch}}, \quad \forall t \geq 1 \tag{3.15}$$

$$SOC^{min} \leq SOC(t) \leq SOC^{max}, \quad \forall t \tag{3.16}$$

$$0 \leq u_{dch} + u_{ch} \leq 1, \quad \forall t \tag{3.17}$$

3.2.6 PV generation

The next three Equations, 3.18 to 3.20, are for the PV generation array. The PV array upper and lower limitation is in Equation 3.18. The two Equations, 3.19 and 3.20, refers to the minimum and maximum values that the PV generation in each time slot may have for the robust optimization problem.

$$P_{pv}^{min}(t) \leq P_{pv}(t) \leq P_{pv}^{max}(t), \quad \forall t \tag{3.18}$$

$$P_{pv}^{min}(t) = P_{pv}^{avg}(t).(1-\alpha), \quad \alpha \in [0,1], \forall t \tag{3.19}$$

$$P_{pv}^{max}(t) = P_{pv}^{avg}(t).(1+\alpha), \quad \alpha \in [0,1], \forall t \tag{3.20}$$

3.2.7 Robust Optimization Programming Model

The next equations are relative to the robust optimization programming model formulation for the solar PV generation uncertainty. Due to the fact this is a maximization problem of the DR aggregator profit, for the formulation of the RO model we need to minimize the total PV generation of the day according to the budget of uncertainty value Γ, defined as an integer parameter, which value may fluctuate between 0 and T (total number of time slots considered), which in this case $T = 24$.

If Γ value is 0, we are ignoring the effect of the uncertainty parameter and we obtain the results for the deterministic model considering the $P_{pv}^{max}(t)$ in all time slots, resulting in the best case scenario for the DR aggregator profit maximization. If we consider the $\Gamma = T$, we are taking into account the PV generation uncertainty in all time slots, resulting in the worst case scenario for the DR aggregator, so we get the minimum value of profit maximization possible. The uncertainty interval for $P_{pv}(t)$ is defined in Equations 3.18 to 3.20. Considering α a percentage of the average PV generation of 20 scenarios of production.

In order to obtain the Equations 3.21 to 3.28, it is considered 2 dual variables $\xi(t)$ and β which are inserted in the Equation 3.21 with negative signs, this happens in order to be possible to insert the PV uncertainty parameter in the balance equation of the maximization model 3.30. Changing the signal it is possible to just maximize the profit, maximizing the total PV generation deviation, minimizing the PV generation at the same time respecting the considered Γ value.

Equation 3.21 is calculating the total PV generation of a day considering the uncertainty budget. For each hour the RO is using the maximum PV generation. If $\Gamma = 0$ and knowing that this problem is a maximization problem, maximizing the profit of DR aggregator the model is considering the best case scenario for the PV generation where at every hour the generation is maximum.

Increasing the Γ, the model is considering the worst case scenarios of production for the number of time slots equal to Γ so the problem became a Max Min type. To solve that, and to transform this into a maximization type problem, it is added two dual variables that are limited in Equations 3.23 to 3.25.

$$P_{pv}^{Total} = \sum_{t=1}^{T} [P_{pv}^{max}(t).x(t) - \xi(t)] - \Gamma.\beta, \quad \forall t \tag{3.21}$$

$$P_{pv}^{Total} = \sum_{t=1}^{T} P_{pv}(t), \quad \forall t \tag{3.22}$$

$$\beta + \xi(t) \geq (P_{pv}^{max}(t) - P_{pv}^{min}(t)).y(t), \quad \forall t \tag{3.23}$$

$$\xi(t) \geq 0, \quad \forall t \tag{3.24}$$

$$\beta \geq 0 \tag{3.25}$$

$$y(t) \geq 0, \quad \forall t \tag{3.26}$$

$$x(t) \leq y(t), \quad \forall t \tag{3.27}$$

$$x(t) \in \{0,1\}, \quad \forall t \tag{3.28}$$

3.2.8 Objective Function

Equation 3.29 is the objective function (OF) of the model, it is responsible to maximize the profit of the DR aggregator. The first term of the OF obtain the income from selling DR with fixed DR contracts to the purchasers. The second term the income of selling DR using DR option agreements to the purchasers followed by the penalty fees if the DR aggregator cancels that agreement. The last term, represents the rewards that the DR aggregator needs to pay to the consumers that assign to the reward based DR four their load reduction. Maximizing the OF is the same that maximizing the PV generation, the model is minimizing the PV generation at the same time that the objective function is being maximized because of the inserted constraints of the RO model.

Furthermore, Equation 3.30 represents the energy balance of the system between the demand and supply of energy. In this equation, is integrated the power charged and discharged of the BESS and the solar PV generation at each hour considering the uncertain nature of this RER, using the RO programming model like it was explained in the last section.

The first and second terms of this Equation 3.30, are related to the DR traded by the DR aggregator with the purchaser using DR fixed contracts and DR option agreements, respectively. The third term is related to the DR traded by the consumer with the DR aggregator using reward-based DR program. The fourth, is the load difference resulted from the use of TOU program at each hour. The fifth and sixth terms are related to the power that is used to charge and the power that is discharged of the BESS at each hour of the day.

Finally , the last term is related to the PV production at each hour of the day and it can be considering uncertainty if in the RO programming model, the budget of uncertainty upper than zero or not if this budget of uncertainty is equal to zero. The following constraints are related to all the variables that are inserted in the OF and in the balance equation.

Objective Function: $Max \quad B$

$$= \sum_{t=1}^{T} [\sum_{f=1}^{N_f} \sum_{b=1}^{N_b} [P_{f,b}^{DR}(t).\lambda_{f,b}^{DR}(t)] + \sum_{op=1}^{N_{op}} [P_{op}^{DR}(t).\lambda_{op}^{DR}(t) - (1 - v_{op}^{DR}(t)).f_{op}^{pen}(t)] - \sum_{j=1}^{N_j} PF(t).\overline{P}_j^{DR}(t).R_j^{DR}(t)] \tag{3.29}$$

Subjected to:

$$\sum_{f=1}^{N_f} \sum_{b=1}^{N_b} P_{f,b}^{DR}(t) + \sum_{op=1}^{N_{op}} P_{op}^{DR}(t) = P^{DR}(t) - TOU(t) - P_{ch}(t) + P_{dch}(t) - P_{pv}(t), \quad \forall t \tag{3.30}$$

In addiction to the balance constraint, to the objective function equation is added as constraints associated to Fixed DR contract Equation 3.2, that is associated to Fixed DR contracts. Equation 3.4, associated to DR option agreements. Equation 3.5, associated to TOU program. Equations 3.6 to 3.10, associated to the reward-based DR program. Equations 3.11 to 3.17 associated to the BESS. Equations 3.18 to 3.20, associated to the PV generation model. Equations 3.21-3.28, associated to the robust optimization programming method.

Chapter 4

Numerical Studies

In this chapter, it will be analysed the results from the model that was developed and explained in the last chapter. The main objective is to observe the impact in the DR aggregator profit of PV generation uncertainty and the electrical energy storage system behaviour in order to notice the advantages by introducing them and also, to analyse the DR trade behaviour between the consumers, DR aggregator and purchasers using the DR programs that this aggregator contains.

Firstly, there is a data preparation section, that include all the data that was used in this model for the solar PV generation, BESS and DR programs. Secondly, it is analysed and explained the results obtained from the deterministic model developed comparing the result between three different cases of the system. The first case composed only with the DR aggregator and correspondent DR programs for the consumers and purchasers. In the second case is introduced the BESS model in the demand side to the first case, and finally, the third case where it is integrated the PV generation system on the consumer side to case 2.

This model was developed from a base model that is explained in reference [90], that corresponds to the case 1 of the deterministic model formulation. This reference model, consists in a maximization of the profit of a DR aggregator with different DR programs, and different types of Consumers. From that, the objective was to apply PV generation and a BESS in the consumer side to see the impacts in the deterministic model profit of the DR aggregator.

Finally, it was applied a RO program that was developed and is explained in the last chapter with the objective to insert PV generation uncertainty into the model. It is analysed the behaviour of the RO model applied, in order to see the influence of the PV generation uncertainty in DR aggregator profit and the behaviour of the active actors of the system, such as DR programs, BESS and PV generation.

4.1 Data Preparation

This program is formulated as a linear program (LP) and was used the CPLEX solver under General Algebraic Modeling System (GAMS) to obtain the results. To study the proposed model, different values of uncertainty budget was inserted to the RO model, in order to simulate the PV generation uncertainty of the PV-battery system. The simulation of the proposed model was ran by a PC with 16GB RAM and 2.21 GHz CPU.

For this model is considered two distinctive time periods of a day, the on-peak period, which is considered from 9am until 10pm and the off-peak period are the remaining hours of the day. In addiction, in this model are considered three different types of consumers, which are residential, commercial, and industrial, each one with different characteristics of consumption.

Furthermore, for the PV array, was imported 20 scenarios of PV production from Belgium measures and up scaled values using the website [91], and from the average of all 20 scenarios of generation resulted the p.u. values of a possible scenario of production dividing the PV array average for the maximum nominal capacity of PV generation of the forecast values.

Finally the data for demand response was extracted from [90]. The load of a day is taken into account, with to different periods, on peak from 9am to 10pm and off peak the remaining hours. The DR is being bought from the consumers by the DR aggregator and then it is being sold to the purchasers by the aggregator during the on peak hours and during the off peak periods the DR is by the customers to the DR aggregator and then it sell again to the consumer the DR.

In Figure 3.1, it is possible to observe that are considered three different types of consumers, which are commercial, industrial and residential. The DR aggregator obtain the DR through 2 different DR programs that are applied to the consumers. One of them is the reward-based DR and the other one, time-of-use program. Furthermore, the aggregator trades the obtained DR to the purchasers considering 2 different forward contracts, DR option agreement and fixed DR contracts.

- **Fixed DR contracts**

  The fixed DR is one of the two forward contracts that DR aggregator make with the purchaser, data contains, 6 blocks for on-peak periods with 90kW of maximum demand, and another 6 blocks for off-peak periods with 30kW of maximum demand with the prices in Table 4.1. The trade between aggregator and purchaser needs to be executed accordingly to the block chosen that have different price values for off-peak periods and on-peak periods.

Table 4.1: Fixed DR contracts price for DR option agreements in $/kWh

	On-peak	**Off-peak**
Block 1	36	15
Block 2	37	16
Block 3	38	18
Block 4	39	20
Block 5	40	21
Block 6	41	23

- **DR options agreements**

  DR option agreements, the other forward contract, contains 8 different agreements for the whole day, 4 for on-peak periods and another 4 for off-peak periods. The DR aggregator has the right to cancel the agreement but it is endorsed with the penalty fee that must be paid to the purchaser. This penalty is equal to 10% of the whole value. The trade between the DR aggregator and the purchaser it's executed with the possibility at every hour chose one of the 4 different options. In Table 4.2 and 4.3 are the demand of all 4 options that could be traded between aggregator and purchaser and the respective prices.

Table 4.2: Pool order demand for DR option agreements in kWh

	On-peak	**Off-peak**
Option 1	50	-50
Option 2	50	-30
Option 3	50	-30
Option 4	50	-25

Table 4.3: Pool order price for DR option agreements in $/kWh

	On-peak	**Off-peak**
Option 1	34	21
Option 2	37	20
Option 3	36	22
Option 4	35	18

- **TOU program**

  TOU prices for each consumer are derived from retail tariffs from reference [92]. The elasticity matrix for each type of consumer is provided in Table 4.4, where the values variate with the consumer type and the time period.

Table 4.4: Elasticity matrix for TOU program

		On-peak	**Off-peak**
Residential	**On-peak**	-0.15	0.05
	Off-peak	0.02	-0.03
Commercial	**On-peak**	-0.16	0.06
	Off-peak	0.03	-0.04
Industrial	**On-peak**	-0.2	0.1
	Off-peak	0.07	-0.08

- **Reward-based DR**

  For reward-based DR programs the participation's level considered for each type of consumer is in Table 4.5. Each consumer type have 25 step blocks, represented in Figure 4.1. From that steps they can chose reduction levels of loads during the day but only one per hour. Each step is associated with incentives that consumers have to receive, represented in Figure 4.2, at on-peak periods the incentives are the same for all three types of consumers but different values for off peak periods. This data was extracted from [90].

Table 4.5: Participation level of the consumers at on-peak and off-peak periods in RWDR program.

	On-peak	**Off-peak**
Residential	0.497	0.642
Commercial	0.506	0.506
Industrial	0.481	0.494

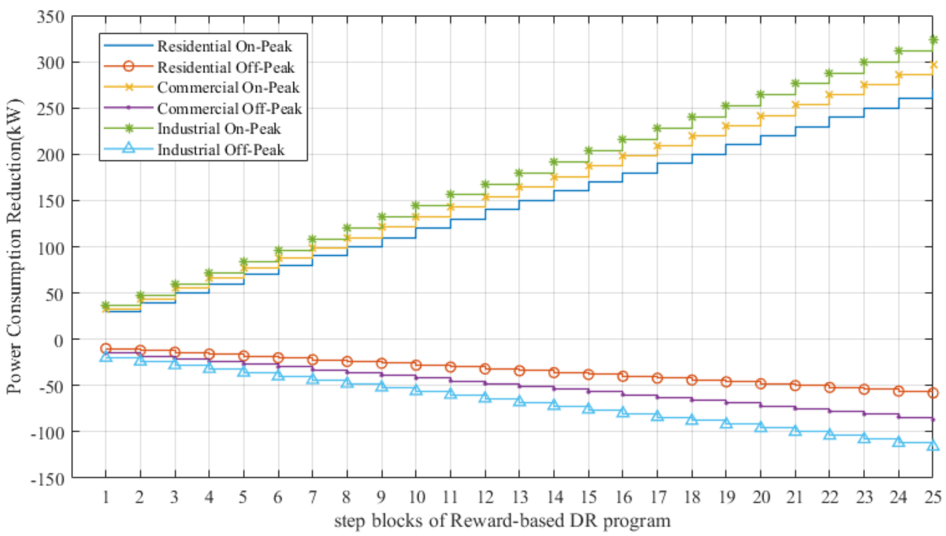

Figure 4.1: Load reduction of all 25 steps for both on-peak and off-peak periods for all three types of consumers in kW.

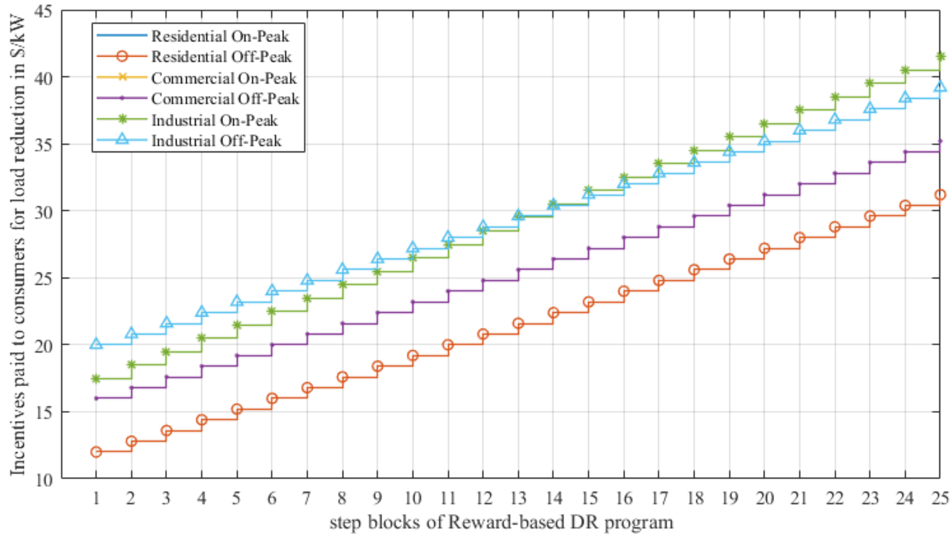

Figure 4.2: Incentives in dollar per kW of load reduction for all 25 steps of both on-peak and off-peak periods for all types of consumers.

- **PV generation**

  For PV generation in deterministic model the values was obtained from extracting 20 case scenarios of production, measured and upscaled, from Belgium and then this profile was used for our 500kW installed PV generation on the consumer side. Figure 4.3, is the PV generation profile used in the deterministic model for one day.

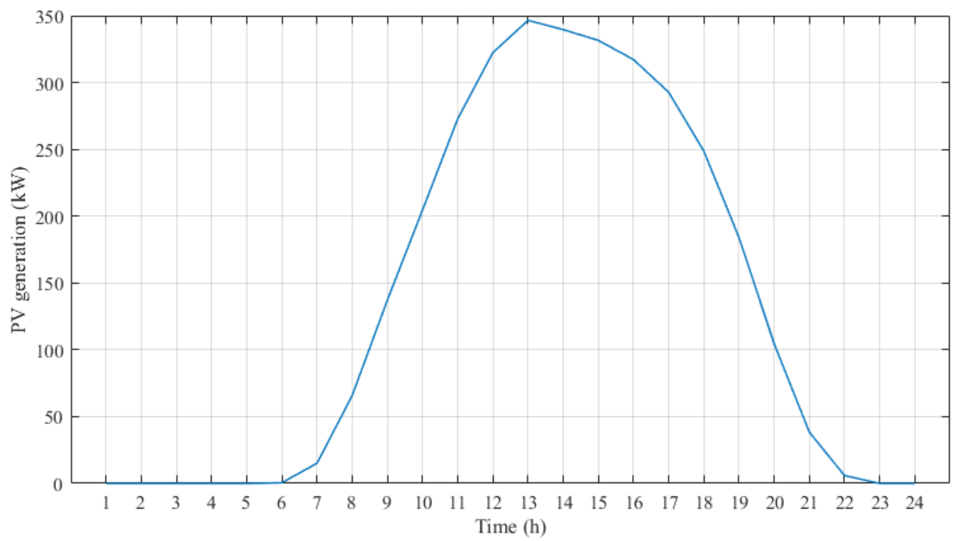

Figure 4.3: PV generation scenario used in the deterministic model.

- **BESS Model**

For the electrical energy storage system model was used the specifications that are in Table 4.6. The P_{dch}^{max} and P_{ch}^{max} values are related to the maximum power rate that the battery could be discharged and charged per hour, respectively. SOC^{min} and SOC^{max} is related to the minimum and maximum energy that could be accumulated in the battery in this battery the SOC^{min} is 20% of the SOC^{max}. Finally, η^{dch} and η^{ch} are the efficiency rates for discharging mode and charging mode of the battery, respectively.

Table 4.6: BESS model scalars values.

P_{dch}^{max}	25 kW/h
P_{ch}^{max}	25 kW/h
SOC^{min}	100 kWh
SOC^{max}	500 kWh
η^{dch}	0.8
η^{ch}	0.85

4.2 Deterministic Model Results

Considering the deterministic model for the DR aggregator, it is analyzed 3 different case scenarios that are resumed in Table 4.7, and include the final results for the DR aggregator profit. For case 1 is considered a DR aggregator composed by two different DR programs that are offered to the three types of consumers (residential, commercial and industrial), which are the TOU program and the reward-based DR program, and the DR aggregator interacts with the purchasers using two different types of contracts, fixed DR contracts and DR option agreements.

In case 2 is added the BESS to the system in order to storage energy for future use with the objective to increase the flexibility of the system and the balance between demand and supply, increasing the profit of the DR aggregator. Finally, in case 3 is added solar PV generation to the system and to this case, in the further sections will be applied a RO programming model to introduce the uncertain nature of the solar PV.

Comparing the profit results of all case scenarios, it is possible to say that the integration of the PV-battery system in the consumer side have an huge impact in the profit of the DR aggregator. The PV-battery system increase the flexibility of the consumers so, it is easier for them to shift their demand, because of that the trades of DR increase so, it is possible for the DR aggregator to trade more with the purchasers improving its profits.

Table 4.7: Different case scenarios for the deterministic model.

	DR	PV	BESS	DR Aggregator Profit
Case 1	✓			201967.95 $
Case 2	✓		✓	202389.48 $
Case 3	✓	✓	✓	311720.24 $

4.2.1 DR Results

In this subsection, it will be analyse the results for the three different case scenarios, to observe the impacts that the different cases have on DR trades by DR aggregator with purchasers and consumers, and to justify the results of the DR aggregator profit for all 3 cases.

In Figure 4.4, it is shown the profit of DR aggregator with each DR program for one entire day, in order to understand how the profit values in Table 4.7 are attained. For case 1 and 2, possible to understand that the DR that is traded from the consumers to the DR aggregator is further, sold to the purchaser using fixed DR contracts and DR option agreements with the volume of trades using the first contract much higher than the second. To acquire the DR from the consumers the aggregator needs to pay the incentive to them using reward-based DR programs, which is the negative input of the profit. In addition, the aggregator needs to pay a small amount of penalties to the purchasers resulted from the penalty for cancel the DR option agreement.

The big difference between these two cases and the case 3 is the positive value that is obtained for the reward-base DR program, resulted from the integration of PV generation in the system together with the BESS. The optimal scheduling of the PV-battery system makes that the consumers in some cases the ask for demand from the aggregator is reduced at the on peak hours because of the power available from the PV generation and from discharging the battery. The positive reward-based DR income, is resulted from the increase of demand in some peak hours because of the availability of power supply from the PV-battery system.

In addiction, it is possible to find out that because of the integration of PV generation together with the BESS, the profit from the fixed DR program increase a lot because of, the demand of the consumer is lower when the price is higher, resulted to the available power supply in the consumer side from PV and battery, so the DR aggregator have more DR to sell to the purchasers.

In terms of values for one day, for case 1, results in a income of 160.4 thousands of dollar from the sell of DR using fixed DR contracts and 57.5 thousands of dollar using DR option agreements. For the costs that the aggregator have to pay, in rewards are being paid 16 thousands of dollar to the consumers and the aggregator does not have the need to pay penalties to the purchaser because the agreements where not cancelled.

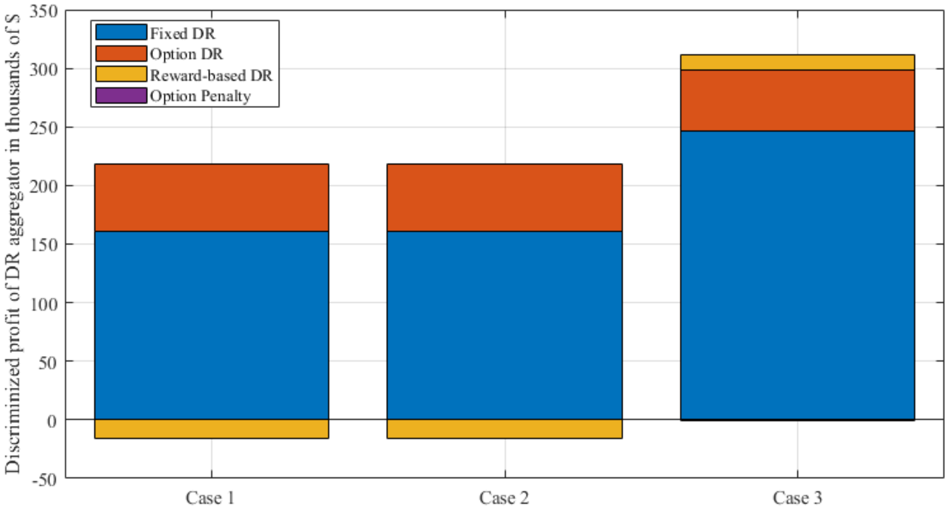

Figure 4.4: Profit from all DR programs integrated in the DR aggregator for all cases in thousands of dollar.

For case 2, the profit have a small increase because of the integration of the BESS. The income got from fixed DR contracts is 160.8 thousands of dollar, from DR option agreements the value of income is the same than case 1. About the costs of case 2 the values are the same that in case 1. Thus, the introduction of the BESS just impacts the fixed DR contracts income this happens because having the battery to discharge at on peak periods, the demand of the consumer is lower when the price is higher so the DR aggregator have more DR to sell to the purchasers, this result in an increase of about 400 dollars per day just by introducing the battery in the end user side.

For case 3, the integration of the PV generation together with the BESS makes that the profit highly increase. The income from fixed DR contracts is 247 thousands of dollars, which means an increase in about 86 thousands of dollar of profit just using FDR contracts. The income from DR option agreements is 51.7 thousands of dollar. Comparative to the other cases, it is a decrease of about 5.8 thousands of dollar, this could be a result of the increase of penalties paid to the purchaser and a more intensive use of the FDR contracts because of canceling the DRO agreement at some hours of the day.

The cost to pay in rewards to consumers become now an income because of the excess of PV production that is sold to the DR aggregator. This income is 13 thousands of dollar. The penalty fees paid to the purchasers by canceling the DRO agreements at some hours of the day are 532 dollars per day.

4.2.1.1 Fixed DR Contract

In Figure 4.5, it is possible to see that the introduction of the PV-battery model have an huge influence in the DR sold from DR aggregator to the purchaser at on-peak periods using fixed DR contracts.

This is a result of PV generation that is being used directly to the load or through the battery, increasing the DR amount in the DR aggregator that could be traded with the purchaser. This local power production reduce the demand of the consumers, increasing the DR traded between the consumer and the aggregator.

4.2.1.2 DR Option Agreements

From Figure 4.6 is possible to conclude that the DR option agreements just change with the inclusion of PV generation and just have different values close to the change of consumption period. As it approaches to the on peak period, the traded DR decrease that results from the increase of PV generation, which reduce consumers need to buy energy to the DR aggregator, so the DR aggregator reduce its power purchase to the market.

In the transition from the on-peak period to off-peak period is possible to see a reduction of the traded DR with the purchaser, this results of the reduction of the PV generation, which results in a decrease of the load reduction from the consumers.

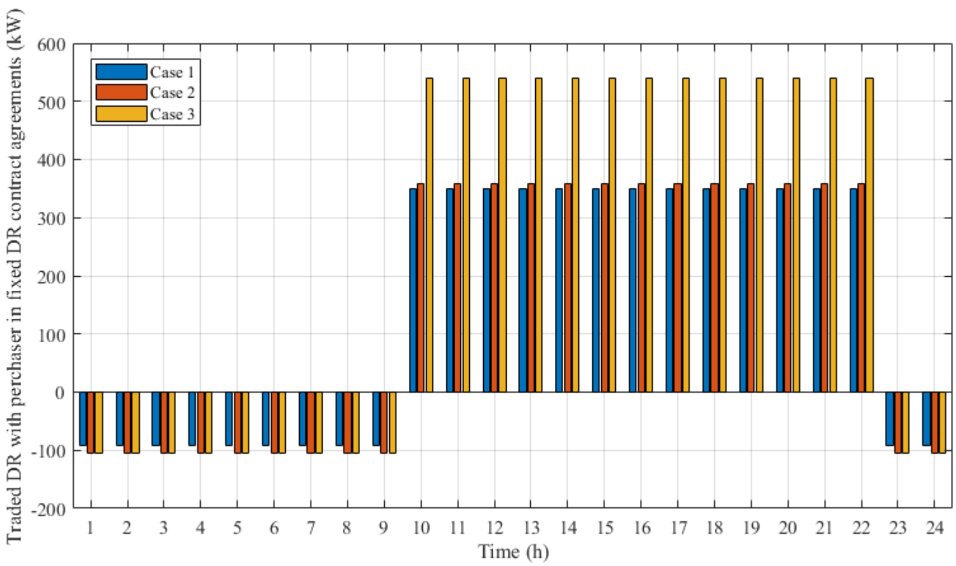

Figure 4.5: Traded DR with the purchaser, using fixed DR contracts

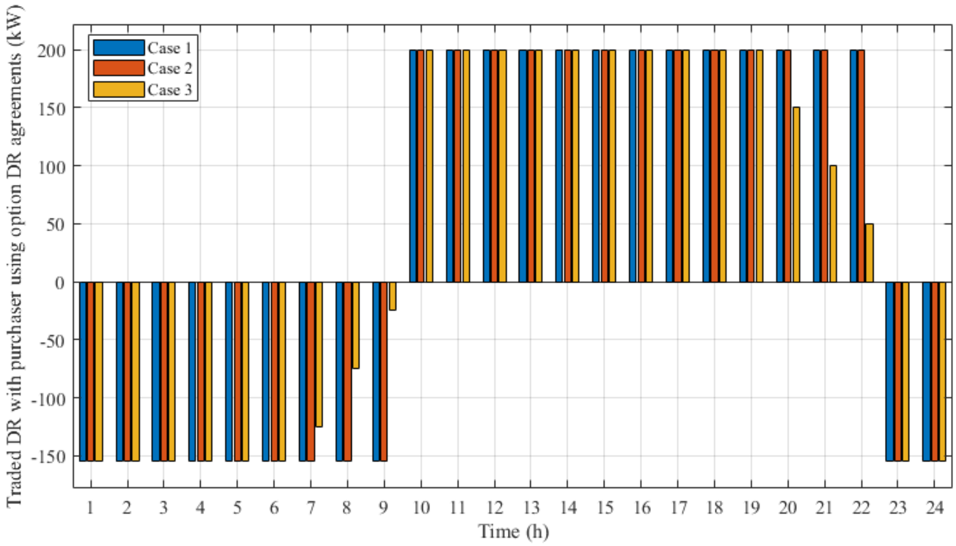

Figure 4.6: Traded DR with the purchaser, using DR option agreements.

4.2.1.3 Reward-Based DR

In Figure 4.7, is possible to observe that, for the reward-based DR program, in case 3, where the PV generation is inserted in the consumer side, a reduction of the traded DR, which means that the consumer does not have the need to reduce their load consumption when the PV is generating power directly to the loads. At the end of the peak hours, when the PV generation is reducing to values close to zero, the load reduction increases in order to compensate the peak demand.

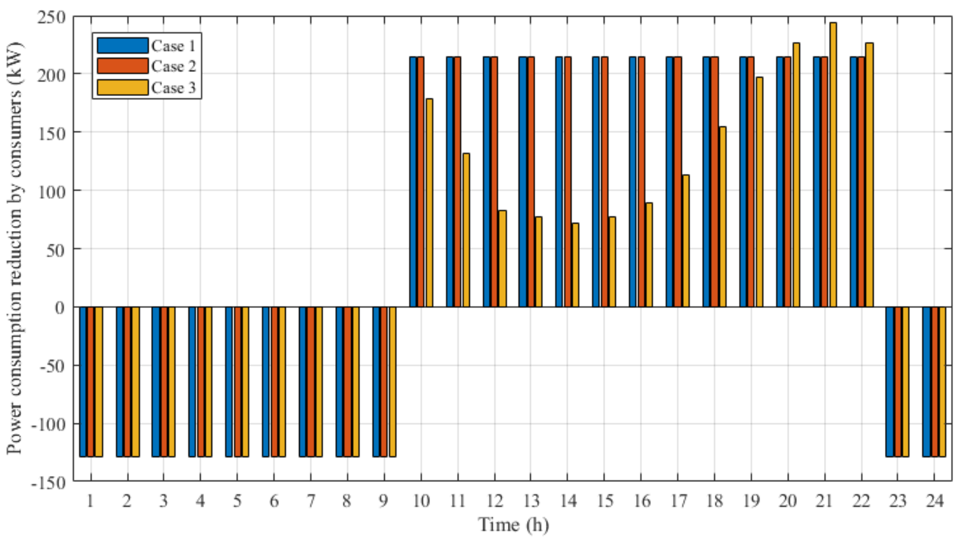

Figure 4.7: Traded DR with the consumers, using Reward-based DR.

In the last time interval before the transition to off-peak period it is possible to see a reduction of the load reduction, this is a result of the BESS discharging to the load in order to compensate the reduction of PV generation at the ending of the day.

4.2.1.4 TOU

From Figure 4.8, it is possible to observe that the TOU traded DR is equal for all the cases. It is obvious that the TOU program incentives the consumers to shift their consumption from on-peak periods to off peak periods. This values result from the difference between the initial demand and the demand after the application of the TOU program, with a reduction of the load at on peak hours and with an increase of the load at off peak hours that compensate the reduction executed at on peak periods.

4.2.2 Battery Energy Storage System

For the BESS, in Figure 4.9 is possible to observe the state of charge at each hour of the day for case 2 and 3, both of them with the BESS integrated in the consumer side. In Figure 4.10, it is shown the power that is charged or discharged of the BESS at each time interval.

From the analyse of both graphics, is possible to conclude that with the integration of the PV generation in case 3 at the hours of more PV production of the day that matches with the peak period of consumption, the battery start to charge with the surplus of PV generation, that doesn't happen in case 2 because the battery needs to discharge to balance the load with the power supply.

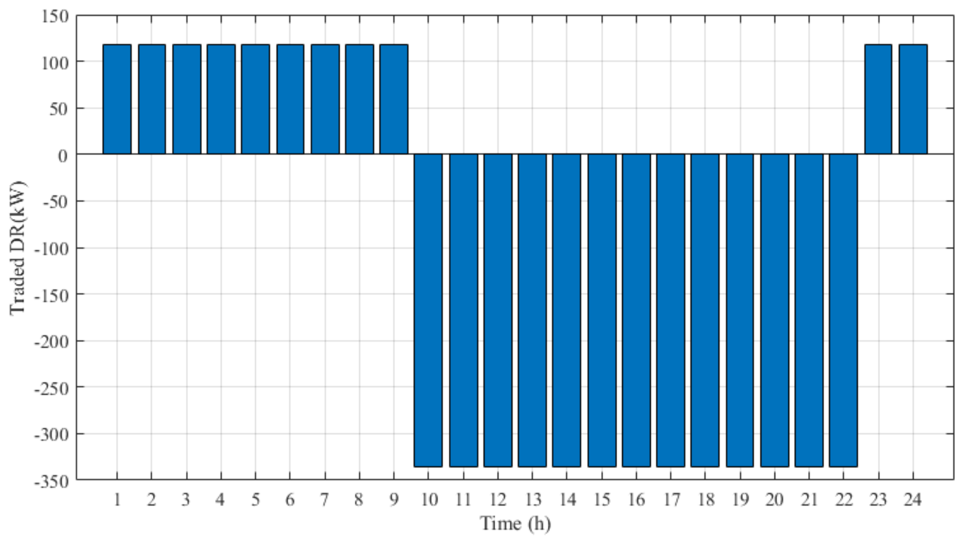

Figure 4.8: Traded DR with the consumer, using TOU.

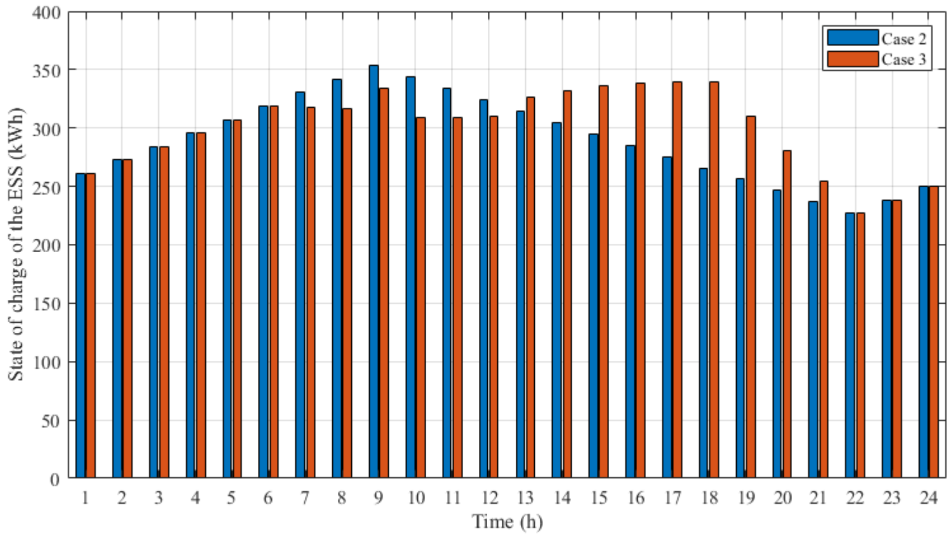

Figure 4.9: State-of-charge of the BESS at every hour of the day (kWh).

In the final hours of the day in the on peak period, we have a large amount of Power that is discharged from the battery this results from the decrease of PV generation in that hours and the lower load reduction that the consumer have comparative to the case 2 like it was seen in Figure 4.7, and the lower DR trade between the DR aggregator and the purchaser using DR option agreements in Figure 4.6 and the same amount of DR traded using fixed DR contracts of the hours that we had higher PV generation so, the BESS is compensating the decrease of PV generation trying to maintain the same amount of DR trades with possible.

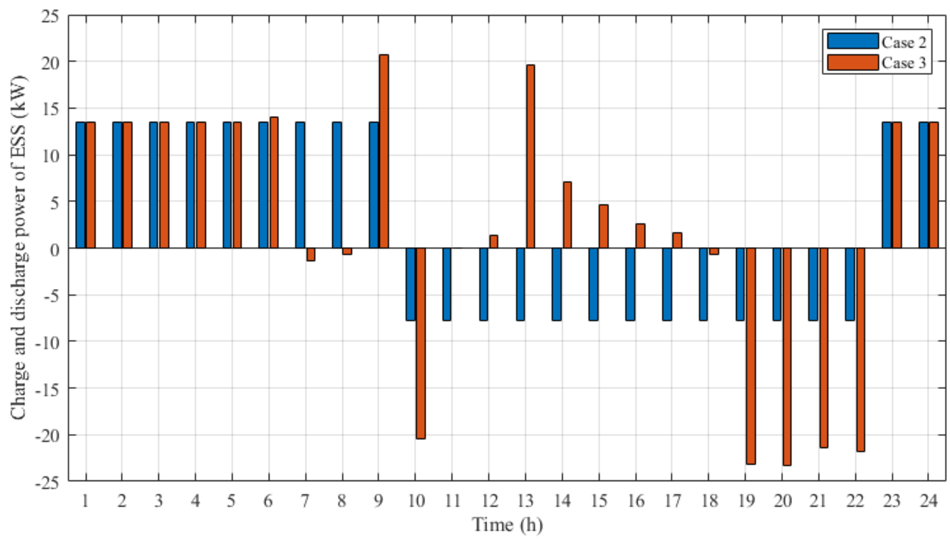

Figure 4.10: Power charged and discharged for different case scenarios in the BESS at every hour of the day (kW).

4.3 Robust Optimization Model Results

For the robust optimization model, it is considered that the budget of uncertainty can takes value from 0 to 24 (Γ). It is also defined that the minimum PV generation is 80% of the average PV generation that was obtained from 20 scenarios of generation and the maximum PV generation possible is 120% of that PV average.

It is possible to find out that, when $\Gamma = 0$, is considered a deterministic resolution of the model using the maximum PV generation for the PV array so in this situation, the profit is maximum with a value of 311.7 thousands of dollar. On the other hand, when it is considered $\Gamma = 24$, the profit is the minimum possible, with a value of 278.3 thousands of dollar, this is due to consider the PV minimum values for every hours of the day, being the worst situation possible. It is possible to conclude that the profit of the DR aggregator is ranging from 278.3 to 311.7 thousands of dollar considering the uncertainty of PV generation.

Analysing the Figure 4.11, between $\Gamma = 0$ and $\Gamma = 12$ approximately, the profit reduction is reversely linear with uncertainty. After around $\Gamma = 12$, the profit start to be a constant distribution this occurs because of the RO program start to input uncertainty in the hours when the sun radiation is lower so, increasing the budget of uncertainty, the deviation of profit are smaller and smaller. First, the model minimize the PV generation in the hours that have more generation to minimize the daily PV generation when maximizing the profit. Increasing the budget of uncertainty the RO programming method starts to act in the hours when the PV generation is low because of the small or none amount of sun radiation. Because of that the deviation of the profit at high values of uncertainty is getting smaller and smaller until being zero.

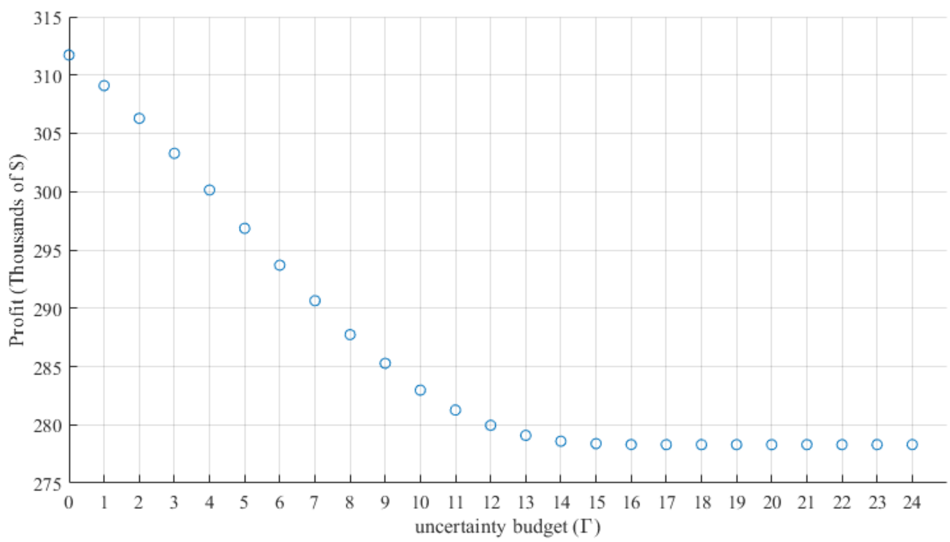

Figure 4.11: Profit of DR aggregator considering the PV generation uncertainty budget.

4.3.1 PV Generation

Observing the PV generation array for the 24 hours of the day, using different values of uncertainty budget, it is possible to verify that when $\Gamma = 0$ it is considered deterministic model values for the PV generation, so the PV generation uncertainty is not taken into account.

Increasing the Γ is the same to increase the uncertainty on the PV generation. Due to that it is possible to see in Figure 4.12 that the RO model starts to minimize the time slots of the day when the sun radiation is higher, around the mid of the day, in order to minimize the total PV generation of the day considering the budget of uncertainty chosen.

Increasing the uncertainty budget value the total PV generation decrease. In Table 4.8 are the values of total PV generation for one day and is possible to see that these values decrease with the increase of uncertainty.

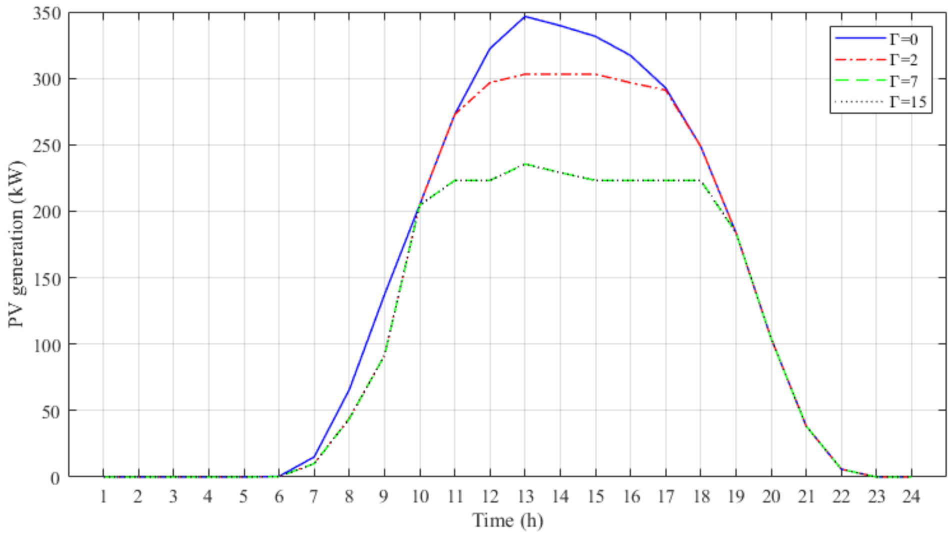

Figure 4.12: PV generation for different values of uncertainty Γ for all time slots of one day.

Table 4.8: PV generation for an entire day using different values of budget uncertainty (Γ) in kW.

Uncertainty budget (Γ)	**Total PV generation (kW)**
0	3227.3
2	2998.6
7	2486.4
15	2153.7
24	2151.5

4.3.2 Battery Energy Storage System

The BESS is used to charge the excess of supply in order to use in the future, improving the flexibility of the consumers. In Figure 4.13, is shown that the state of charge (SOC) of the BESS increase over the first hours of the day, this is a result of the off peak period in that hours so, the battery is only charged, which is verified by figure 4.14. The consumers does not have the need to use the battery to fully supply their load and also because it is accumulating energy when the price is lower to use it when the price of the electricity is higher at on peak periods.

When starts the on peak period the the battery shift to the discharge mode as shown in Figure 4.14, in order to reduce the need of the consumer to increase their demand to the DR aggregator. Using lower uncertainty budget values, in some situation the battery is capable to charge but this only happens for high value of PV generation because with that the load is supplied and the exceed of production goes to the battery. But when the PV curve is decreasing the battery starts to have a more active role in the load supply, compensating the decrease of PV generation, this is demonstrated in Figure 4.14.

During all day, the battery discharge a total of 112.83 kW and charge a total of 165.9 kW for a value of $\Gamma = 0$. For $\Gamma = 7$, the battery discharge 105.3 kW and is charged 154.9 kW. Also, for $\Gamma = 15$, the battery discharge 107.8 kW and is charged with 158.5 kW. For $\Gamma = 15$ the value of charged power increase comparative to $\Gamma = 7$, due to a higher load reduction of the consumer resulted from the decrease of PV generation due to the increase of uncertainty.

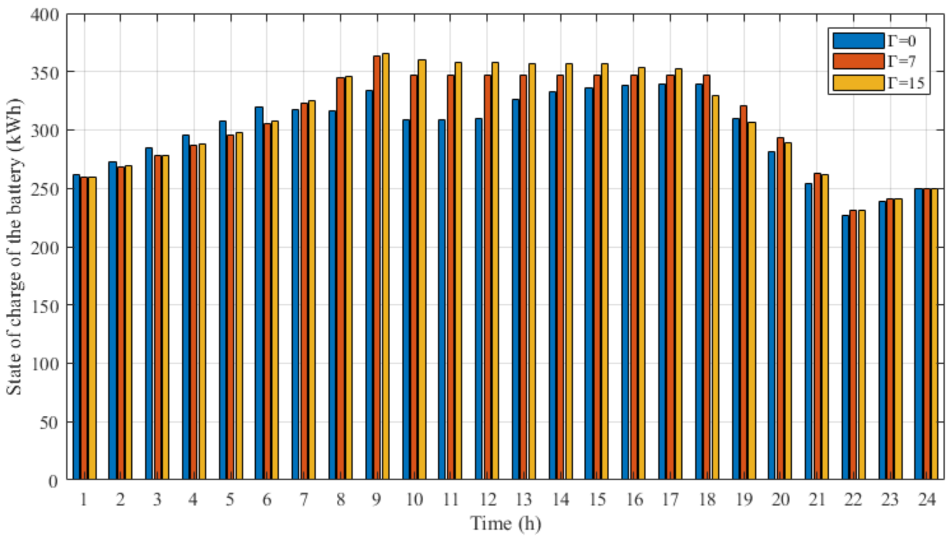

Figure 4.13: Energy stacked in the BESS for each time slot with different values of Γ.

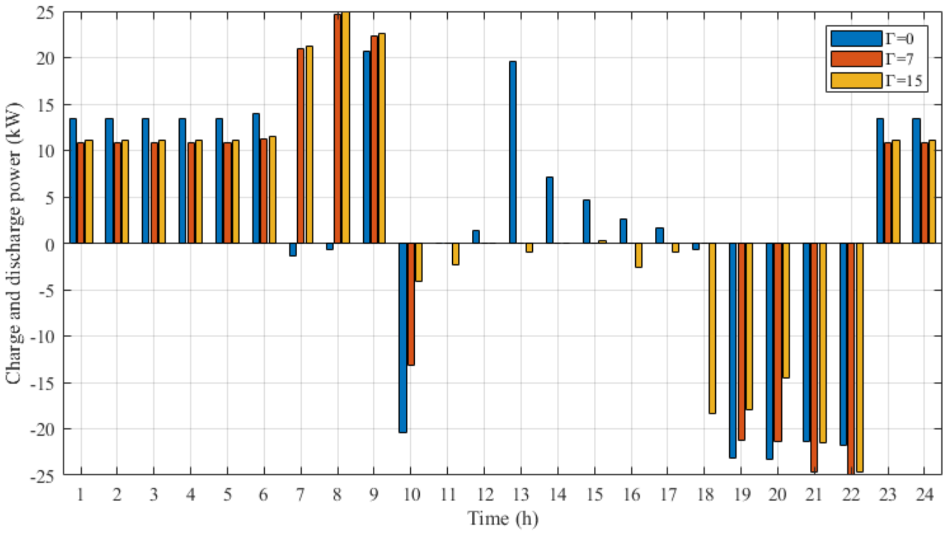

Figure 4.14: Charge (positive values) and Discharge (negative values) power in kW for all time slots with different values of Γ, in the BESS.

4.3.3 DR Results

From the analyze of Figure 4.15, it is possible to see how the profit of the DR aggregator is obtained through the various DR programs. The profit is decreasing with the increase of uncertainty budget. For $\Gamma = 0$, due to the high PV generation, the DR aggregator is receiving income from the reward-based DR program, this happens because of the increase of demand in some on peak hour which is possible due to the high PV supply in the consumer side.

When the PV generation decrease because of the increase of uncertainty, the consumers need to execute load reductions in order to balance the supply with the load so the aggregator pays reward to the consumers which is shown in the figure for $\Gamma = 7$ and for $\Gamma = 15$.

For $\Gamma = 0$ the DR aggregator is receive income from FDR contracts of 247 thousands of dollar, 51.7 thousands of dollar from DR option agreements and 13 thousands of dollar from reward-based DR. In addition it have to pay the cost of 532 dollar to the purchasers corresponding to penalty fees of DRO agreement.

For $\Gamma = 7$ the DR aggregator is receive income from FDR contracts of 247 thousands of dollar, 48.7 thousands of dollar from DR option agreements and needs to pay the cost of 4.8 thousands of dollar, corresponding to the rewards, to consumers from reward-based DR. In addition it have to pay the cost of 803 dollar to the purchasers corresponding to penalty fees of DRO agreement.

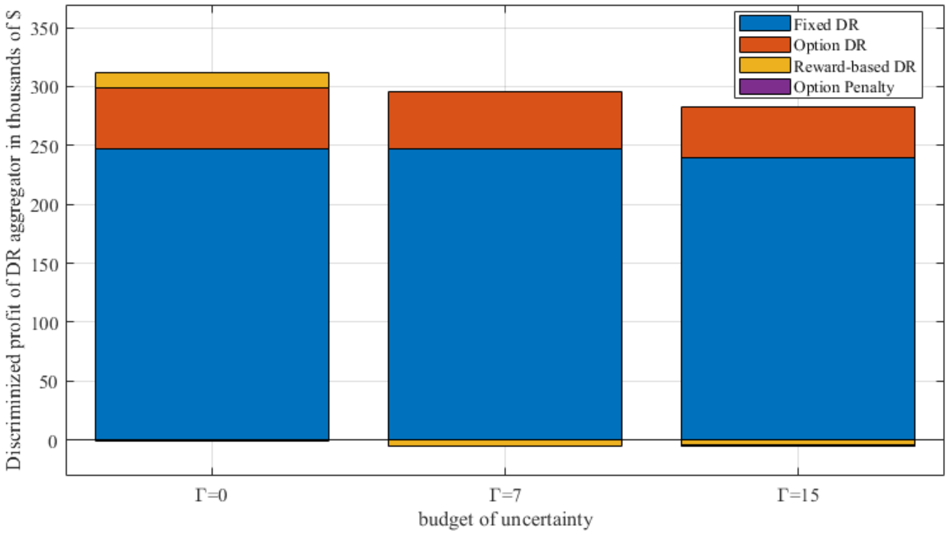

Figure 4.15: Profit from all DR programs inserted in DR aggregator with different values of Γ in thousands of dollar.

For $\Gamma = 15$ the DR aggregator is receive income from FDR contracts of 239.8 thousands of dollar, 43 thousands of dollar from DR option agreements and needs to pay the cost of 4.5 thousands of dollar, corresponding to the rewards, to consumers from reward-based DR. In addition it have to pay the cost of 1.3 thousands of dollar to the purchasers corresponding to penalty fees of DRO agreement.

4.3.3.1 Fixed DR Contracts

The purchasers of DR use fixed DR contracts that are established with the DR aggregator. In Figure 4.16, it is possible to observe that the increase of the uncertainty budget, lead to a reduction of the DR agreement amount sold to the purchaser by DR aggregator.

For each uncertainty budget values the DR traded at on peak is the same for every hour of this period and for the off peak period happens the same. This is a result of the DR contract chosen for all day. For off peak period, the DR aggregator buys from purchaser 105 kW of power and sell 540 kW at on peak periods, at each hour for $\Gamma = 0$.

For $\Gamma = 7$, the aggregator, buys from purchaser 102.3 kW of power and sell 538.1 kW at on peak periods, at each hour, and for $\Gamma = 7$, the aggregator, buys from purchaser 102.7 kW of power and sell 523.5 kW at on peak periods, at each hour.

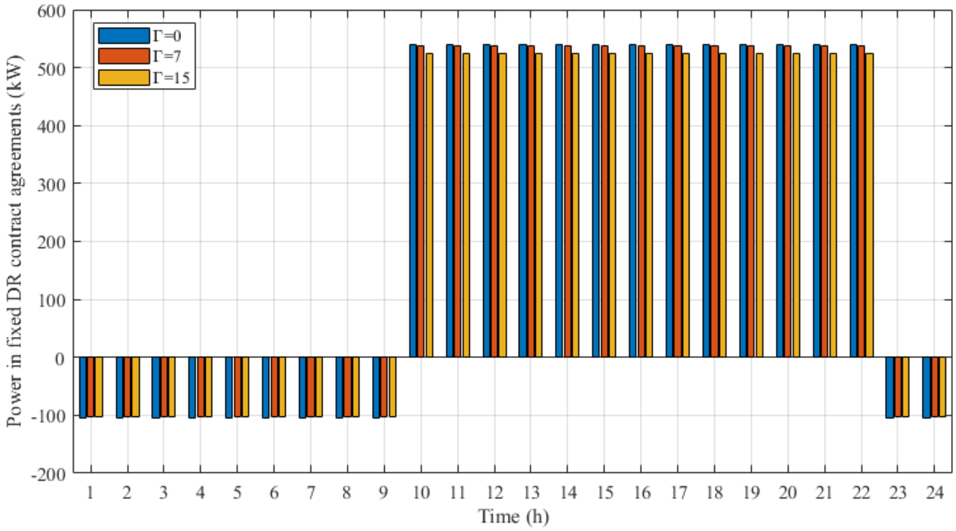

Figure 4.16: Fixed DR contract agreements for every hour of a day in kW, with different values of uncertainty budget in kW.

4.3.3.2 DR Option Agreements

In DR option agreements, represented in Figure 4.17 for three different values of uncertainty budget is possible to see a decrease of power purchased in the off peak period from the DR aggregator when the PV generate start to supply the consumers this happens because of the consumers need decrease to purchase demand at this hours to compensate the PV supply increase.

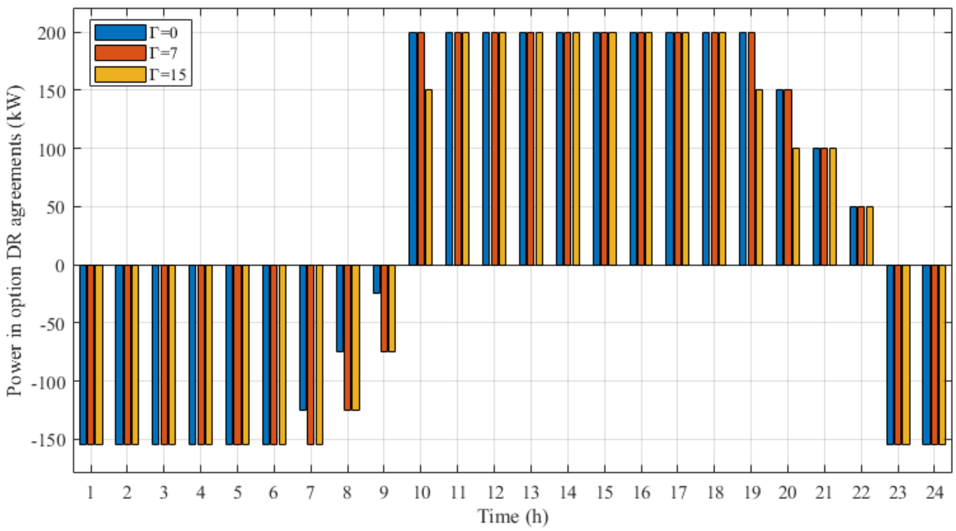

Figure 4.17: DR option agreements for every hour of a day in kW, with different values of uncertainty budget in kW.

At on peak period, when the PV generation starts to decrease, the DR traded with the purchaser also decrease this is a result of the high discharge volume of the BESS at these hours in order to compensate the reduction of PV generation and to maintain the balance of the demand with supply of the consumer.

4.3.3.3 TOU Program

The behaviour of time-of-use program implemented is in Figure 4.18. The program encourages the consumers to transfer demand from on-peak to off-peak periods where the prices are much more attractive to consumers, in order to reduce the congestion and losses of energy at on peak periods. The results of TOU program do not modify for different uncertainty budget levels.

It is possible to observe that at on peak periods the difference between the initial demand and the demand after applied the TOU tariffs is positive so the DR aggregator is increasing the supply to consumers in 117.9 kW per hour. At on peak period, the consumer is decreasing the demand in 335.9 kW per hour.

4.3.3.4 Reward-Based DR Program

In figure 4.19, is represented the results for the reward-based DR program of the load reduction of the consumers at each hour and for different values of budget uncertainty. During the off peak period, the values of increased load in order to compensate the decrease at the on peak period are the same for all hours and Γ. At on peak period, with the increase of PV generation the load reduction decrease and the opposite happens.

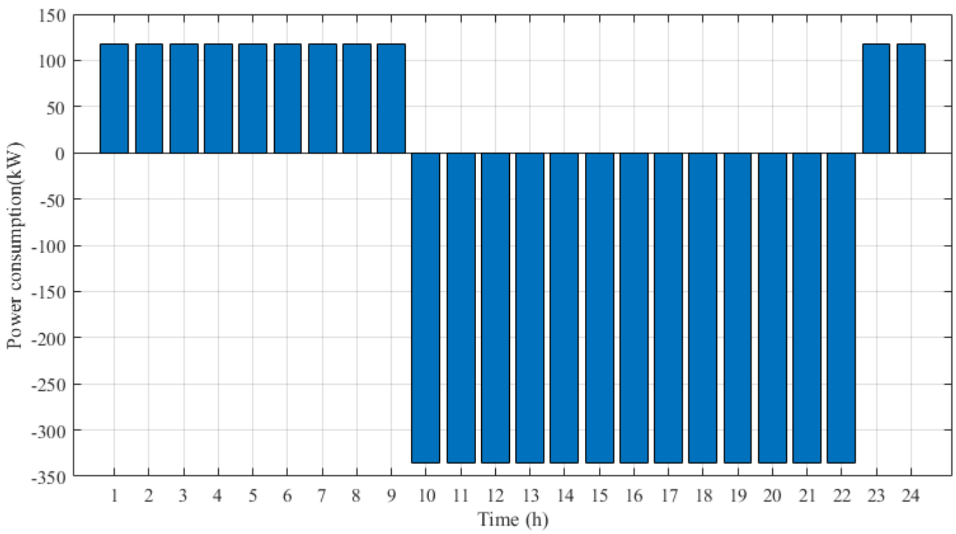

Figure 4.18: Time-of-use program results in kW.

When the PV generation curve is decreasing in this on peak period. For low values of Γ, the need to decrease load of the consumer is minimum so, when $\Gamma = 0$ for example, knowing that in this situation the PV generation is maximum, the values of DR traded with the aggregator at on peak period are minimum, so the DR increased at off peak periods is greater than the DR decreased at on peak periods. This justify the results of Figure 4.15, where the this program is resulting in income to the DR aggregator profit.

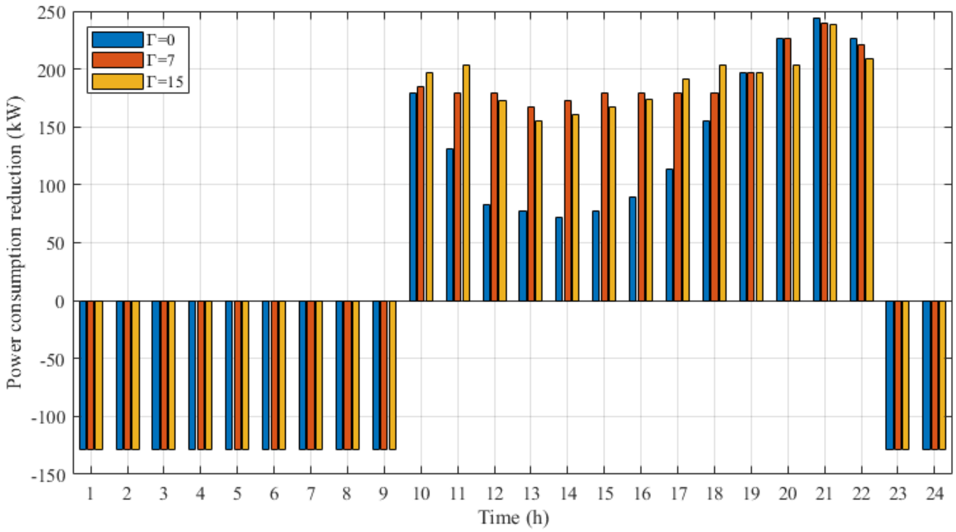

Figure 4.19: Load power reduction by consumers in kW, for reward-based program at every hours of the day for different budgets of uncertainty (Γ).

Chapter 5

Conclusion and Future Research

5.1 Conclusion

With the development of this work, some of the challenges that RER inflict in the power system was addressed as an attempt to solve them. For the utilization of PV generation as a distributed energy resource, the addition of energy storage systems was essential to overcome the uncertain nature of this resource. The ESS, integrated in the model, was considered as batteries, had the objective to compensate the variability of PV generation during the day, improving the load supply flexibility of the energy system with an easier balance between supply and demand.

As it was explained in the results section, the BESS have an huge impact to supply the load when the PV generation starts to decrease because of the low irradiation of the sun at the end of the day at demand on-peak hours. At these hours, the balance between the power supply and the demand is endangered so the BESS discharge to the load in order to reset that balance. This reaction of the BESS is possible because, during the day, when the PV generation exceed the demand, that excess was used to charge the BESS. In addiction, in some cases, the BESS was also charged at off-peak period, in order to avail of the lower electricity prices.

The integration of DR programs through aggregators, used for all types of consumers, such as residential, commercial and industrial, is also a beneficial resource for the energy system. These DR programs that are engaged to the DR aggregator, motivates the participation of the consumers using financial rewards that are paid to them in exchange of consumption reduction by the consumer through the reward-based DR program.

Furthermore, with TOU programs the DR aggregator impose tariffs that promote the shift of consumption from on-peak to off-peak period, under the elasticity limits of each consumer. These programs, improved load consumption flexibility of the energy system, helping in the integration of RER such as, solar PV.

In addiction, with the aggregation of demand and their sold as a whole to the ISO, increase the influence that the consumers have in the electricity market price, because if the demand at on-peak period decrease substantially the losses and congestion in the grid will decrease, improving the reliability and security of it so, the power system does not need new investments in power generation or transmission and distribution lines capacity, reducing the electricity prices.

The main objective of this work was to maximize the profit of a DR aggregator. Residential, commercial and industrial consumers could engage to this aggregator through reward-based DR programs and TOU programs, and was also integrated PV generation and BESS in the end-user consumer side. The integration of PV generation and BESS, resulted in a high increase of the aggregator profit. The flexibility improvements in the demand side induced by the PV generation and BESS increased the amount of DR traded between the aggregator and consumer which resulted in a larger amount of DR that the aggregator could sell to the purchasers through fixed DR contracts and DR option agreements.

To consider the PV generation uncertainty in the model was developed a RO programming model. This model, in which was possible to vary the uncertainty budget Γ, simulate the variations of PV generation that occur in the real world. For high values of PV generation that was obtain when the budget of uncertainty was low, the trades of DR between all the participants of the system increased, and also the SOC of the battery. In some cases with a high value of PV generation, the consumers even increased their consumption at on-peak period, creating no impacts to the energy system, since this demand was self supplied by the PV and BESS, integrated in the consumer side.

To conclude, the actual state of transition of the power system, with the objective to open path to a large integration of RER, will bring to the consumer an huge responsibility. With the transition from a centralized power system to a decentralized one, the consumer is becoming an active actor of the system, which their consumption action have an impact in all the other elements and participants of the energy system. With this work, was proposed a possible solution to promote the strict usage of the resources and to improve the flexibility and reliability of the power system.

5.2 Future Research

From the work that was developed in this thesis, it would be interesting to develop this model for microgrid or smart grid application considering all the variables of grids like voltage drops, power flows, power losses, power factor compensations, etc., and also the addiction of information and communication technology, smart meters and control systems for the development of a complete and proper smart grid.

Furthermore, it would be appealing, the addiction of other RERs for power generation in this model to see the impacts that a other resources have on the behaviour of the model, such as wind or biomass, and also the use of other types of DR programs such as, RTP or CPP.

In addiction, in this model just was considered the PV generation uncertainty, for future works, can be introduced the participation uncertainty by consumers, in the DR programs, and also the electricity market price uncertainty using, robust optimization or stochastic optimization methods.

Finally, another useful future application and development of this work is the application to the power market, in order to see the impacts that the DR aggregator, the BESS and the PV generation have on the electricity market price.

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