FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO

Optimal Demand Response Program for Flexible Ramp Markets

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January, 2018

Resumo

Com o aumento da integração das energias renováveis no mercado eléctrico devido ao crescimento das preocupações ambientais, surge a necessidade de aumentar a flexibilidade do sistema devido não só à variabilidade da oferta mas também devido à natureza estocástica e muitas vezes imprevisível dos recursos renovavéis, o qual origina uma redução do nível de flexibilidade existente através do deslocamento das unidades convencionais devido à prioridade da absorção e despacho dos recursos renováveis.

Desta forma, as unidades convencionais devem iniciar, desligar e acelerar / desacelerar com maior frequência para preservar o equilíbrio do sistema em tempo real, o que pode levar a deterioração dos mecanismos das unidades, devido ao choque térmico, fadiga do metal, corrosão, erosão ou até degradação devido ao calor. Para superar esta questão, foi proposto adicionar os custos de rampa aos procedimentos da programação de geração com o objetivo de compensar as perdaseconómicas e técnicas das unidades de geração. A inclusão dos custos de rampa no programa diário de despacho/afetação foi estudada em outros trabalhos bem como, os efeitos da natureza variável das unidades de geração renovável sobre os custos de rampa das unidades térmicas. Os custos de rampa foram incorporados ao problema de programação de geração na presença da incerteza proveniente da geração renovável.

No entanto, nos trabalhos referidos verifica-se que não foi realizada nenhuma modelação do mercado de rampa. Na atualidade, a fim de compensar a perda parcial dos geradores convencionais e incentivá-los no fornecimento de uma rampa flexível para cima/baixo, foi desenvolvido um mercado denominado "flexiramp" no Operador Independente do Sistema (ISO) da Califórnia (CAISO) e "rampa capacitiva" no Midcontinent ISO (MISO), juntamente com os mercados de energia e de reserva, a fim de assegurar a capacidade de reserva proporcionada pela mistura da geração para lidar com as variações súbitas da carga total.

A criação das ferramentas designadas por rampa flexível em mercados de ISO em tempo real foi investigada com um conjunto de pressupostos simplificados, tais como a omissão das restrições de transmissão e assunção das decisões pré-definidas para o dia seguinte. A formulação matemática para a compensação dos mercados de energia, e da introdução da definição da rampa flexível para o dia seguinte foram também já propostas.

Nestas, os autores discutiram o papel da participação dos veículos elétricos no mercado de rampa, enquanto trataram da avaliação dos impactos da modelagem do sistema de entrega de gás natural e da resposta da procura na implantação da rampa flexível. Apesar dos relatórios mencionados na literatura, encontrar os melhores programas de resposta à procura nos mercados de rampa flexíveis não foi abordado. Desta forma o objetivo do presente trabalho passa pelo estudo das rampas flexíveis no contexto do mercado eléctrico por forma a aumentar a flexibilidade do sistema juntamente com a optimização através de programas DR.

Palavras Chave

Energias Renováveis, Flexibilidade das operações, Integração Eólica, Programação Estocástica,Programas de *Demand Response*, Poluição atmosférica

Abstract

The augmented renewable penetration due to the growth of environmental concerns increases the necessity of additional flexibility because of supply variability, and it reduces the existing flexibility level by displacing with conventional units due to the priority in dispatch for the renewable resources. Therefore, conventional units have to start-up, shut-down and ramp up/down more frequently to preserve the system balance in real-time which may result in common damage mechanisms such as thermal shock, metal fatigue, corrosion, erosion and heat decay.

To overcome this issue, it has been proposed to add the ramping costs into the generation scheduling procedure with the aim of compensating the economic and technical losses of generation units.

The inclusion of ramping costs in the day-ahead scheduling has been studied as well as the effects of the variable nature of renewable generations on ramping costs of thermal units. The ramping costs have been incorporated into the generation scheduling problem in the presence of uncertain renewable generations.

However, the mentioned works have not modeled the ramp market. Practically, in order to compensate a partial loss of conventional generators and incentivize them to provide both upward and downwardflexible ramp, a well-functioning market has been developed so-called "flexiramp" in California ISO (CAISO) and"ramp capability" in Midcontinent ISO (MISO) along with energy and re serve markets in order to ensure the rampability of reserve capacity provided by its generation mixture to cope with sudden net load variations.

The creation of flexible ramp products in real-time ISO markets has been investigated with a set of simplified assumptions such as ignoring the transmission constraints and supposing predefined day-ahead decisions. Formulations for the day-ahead energy and flexible ramp markets' clearing have been proposed. The authors in the referred papers discussed the role of electric vehicles participation in the ramp market, and dealt with the evaluation of the impacts of natural gas delivery system modeling and demand response on flexible ramp deployment.

Despite the mentioned reports in the literature, finding the optimal demand response programs in the flexible ramp markets has not been addressed. In this way the goal of this thesis is to study flexiramp in the context of electrical market in order to increase the system's flexibility whilst optimizing DR programs that can help handle the variability of generation and demand of the market.

Keywords

Air pollution, Demand Response Programs, Operation Flexibility, Renewable Energies, Stochastic Programming, Wind Integration,

Acknowledgements

I would first like to thank my thesis supervisor Professor J. P. S. Catalão of the Faculty of Engineering of the University of Porto. I would also like to thank the experts who were involved in the development and validation of this research project: M. Shafie-khah and G. J. Osório. The door to their offices was always open whenever I ran into a trouble spot or had a question about my research or writing. They consistently allowed this thesis to be my own work, but steered me in the right the direction whenever I needed it. Also, without their passionate participation and input, the validation survey could not have been successfully conducted.

I must express my very profound gratitude to my parents, Eulália and Nelson and to my sister, Inês, for providing me with unfailing support and continuous encouragement throughout my years of study, for bearing with me through all the mistakes, fights, and hard times and through the process of researching and writing this thesis. This accomplishment would not have been possible without them.

I need to thank my girlfriend Ana for all the patience, understanding, motivation and kind words through this entire process, I wouldn't have made it if it wasn't for you.

I would also like to acknowledge all of my friends that were with me through these years of study and made this a wonderful experience.

To my godfather Cristhian for all the values passed, to the Zealous Joana, Inês, Ana and Marisa who always looked out for me, to the Enthusiastic Rui Filipe, Vasco and Francisco who always cheered me up, to the Rare friends who are always there for you Teresa, Inês and Rubens, to the Optimistic Luísa and Flávia who always made me secure everything would be alright, to the Dedicated José Tiago, David and Francisco on who you could always count on, to the Outgoing Nuno, Claúdio, Mariana and João Ricardo who were always ready to have fun, to the Zesty José, José Pedro, Érica and João Paulo and to all Electrical Engineering.

Thank you.

Nuno Gonçalo dos Santos

"Whatever you do in this life, it's not legendary, unless your friends are there to see it."

Barney Stinson

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Acronyms

A/S	Ancillary Service program
AMI	Advanced Metering Infrastructure
CAP	Capacity Market Program
CPP	Critical-Peak Pricing
DB	Demand Bidding
DLC	Direct Load Control
DR	Demand Response
DRP's	Demand Response Programs
EDRP	Emergency Demand Response Program
GW	Gigawatt
HVAC	Heating, Ventilation and air-conditioning
IBDRP's	Incentive Based Demand Response Programs
IPP	Independent Power Producers
ISO	Independent System Operator
I/C	Interruptible/Curtailable service
MO	Multi Objective
MW	Megawatt
PBDRP's	Price Based Demand Response Programs
PEV	Plug-in Electric Vehicle
RES	Renewable Energy Sources
RTO	Regional Transmission Organizations
RTP	Real-Time Pricing
SGs	Smart Grids
SUC	Stochastic Unit Commitment
TOU	Time-of-Use
UC	Unit Commitment

Nomenclature

A. Indexes

b,b'	Index for buses
i	Indexes for generation units
j	Index for loads
l	Index for transmission lines
m	Index for segments
p	Index for wind parks
t, t'	Indexes for hourly time periods
h	Index for sub-hourly time periods
s	Index for scenarios

B. Parameters

$d_0(t)$	Initial electricity demand before DR (MW)
$\rho_0(t)$	Initial electricity price before DR ($/MWh)
$C_i(m)$	Slope of the segment m regarding the cost of fuel of each generator i ($/MWh)
C_i^{UC}/C_i^{DC}	Offered cost of up/down capacity reserve ($/MWh)
C_i^{RU}/C_i^{RD}	Offered cost of up/down deployed reserve ($/MWh)
C_i^{FRU}/C_i^{FRD}	Offered cost of upward/downward ramp product ($/Mwh)
C_i^{SU}	Start-Up cost of the generation unit ($)
$C_{p,t}^{wind}$	Cost of the wind power ($/MWh)
C_p^{spill}	Cost of wind spillage ($/MWh)
RU_i/RD_i	Ramp-Up/Down limits (MW/h)
MUT_i/MDT_i	Minimum Up/Down time (h)
DR^{max}	Maximum DR participation level (%)
$E_{t,t'}$	Elasticity of demand
$A(t)$	Incentive at hour t ($/MWh)
$B(t)$	Customer's income
$NB(t)$	Customer's Net Benefit
η_A	Weight coefficient of the incentive
$P_{i,t}^{min}, P_{i,t}^{max}$	Minimum/Maximum output of conventional units (MW)
$P_{p,s,t,h}$	Real-time generation of wind farms (MWh)
$P_{p,t}^{wind}$	Forecasted wind generation of wind farms (MWh)
P_p^{inst}	Power at each wind park p (MW)
R_l	Resistance of the transmission line l (Ω)
$TP_{l,s,t}$	Power flow through the line l in the scenario s at the hour t (MW)
$DFRU_t^{ex}$	Expected nominal hourly upward ramp need (MW)
$DFRD_t^{ex}$	Expected nominal hourly downward ramp need (MW)
$DFRU_{s,t,h}^{RT}$	Real-time upward ramp need (MW)
$DFRD_{s,t,h}^{RT}$	Real-time downward ramp need (MW)
$E_i^{SO_2}$	Emission rate of Sulfur Dioxide of the generator i (Kg)
$E_i^{NO_x}$	Emission rate of Nitrogen Oxides of the generator i (Kg)
$\triangle$	Real-time slot
w_s	Probability of each scenario s
NLC	Load with no cost
$VOLL_j$	Value of lost load j ($/MWh)

C. Variables

SUC_i	Start-up cost of convetional units ($)
ρ_t	Electricity price ($/MWh)
$U_{i,t}$	Binary on/off status indicator
$\rho_t^{LTP/OTP/PTP}$	Electricity tariffs of low-load, off-peak and peak time periods in TOU programs ($/MWh)
dt	Electricity Demand (MW)
$L_{final}(t)$	Final load after DR
$\triangle d(t)$	Changes in electrical demand (MW)
$P_{i,t,m}$	Generation of segment m in linearized cost curve (MW)
$LS_{j,s,t}$	Load shedding of load j (MWh)
$Spil_{p,s,t}^{wind}$	Wind power spillage of wind farms (MWh)
$P_{i,s,t,h}$	Real-time generation of units (MW)
c_i^{RU}/c_i^{RD}	Cost of up/down real-time reserve ($/MWh)
$r_{s,i,t}^{RU}/r_{s,i,t}^{RD}$	Deployed up/down reserve (MWh)
FRU/FRD	Hourly flexible up/down ramp (MW)
$\triangle FRU/\triangle FRD$	Real-time adjusted flexible up/down ramp (MW)
$F_{l,t}$	Energy flow in the line t at the hour t (A)

D. Functions

F_{cost}	Cost Function
$F_{emissions}$	Emissions Function

Chapter 1

Introduction

The following chapter presents a general overview of the work developed for this Master's thesis. First, a brief approach to the topic will be done in order to contextualize the proposed theme. Afterwards, the motivation that originated the interest and the development of this thesis with this theme will be presented, alongside its goals. Finally this thesis structure and some relevant information will be introduced.

1.1 Framework

The challenging environmental targets set by governments and the increase in fossil fuels prices (oil, coal and natural gas) had an impact on the production through renewable energy sources (wind, solar, hydro) in electrical power systems. It is possible, from the outset, to identify the benefits that renewable sources can bring such as the reduction of emissions of pollutant gases, reduction of imports and consequent reduction of energy dependence, as well as the creation of wealth and employment generation [1].

As more and more generation capacity is replaced for different renewable and dynamic energies a new difficulty in energy dispatch planning rises. A characteristic shared by all renewable energy sources is their variability, this is, the amount of energy produced is almost random. In addition, the quantity of energy produced is difficult to predict and in general the profile of renewable generation does not match the electric demand profile. Due to all these aspects variability, unpredictability and the difference of profiles may cause during certain periods, a shortage or excess energy in others [2].

In light of this, the large-scale integration of renewable energy sources with a stochastic / unpredictable behavior, introduces an additional uncertainty in the electrical system. This uncertainty poses new challenges to the Independent System Operator's (ISO) network management, since the objective is to maintain at all times the equality between production and consumption, in order to guarantee the stability of the system [3].

Technological development has led to the use of large-scale wind power generation. In this sense, there is an increase in the share of wind power in the electrical systems of several countries, having gained great prominence worldwide. Figure 1.1, adapted from [4] illustrates the evolution of wind capacity installed in the world in recent times, with a prediction of continuous growth for years to come. In Portugal, wind energy was the technology that has grown most over the years within the renewable energy. However, solar energy in Portugal is still underdeveloped, as it can be seen from the analysis of figure 1.2 adapted from [5].

As mentioned before, a massive integration of renewable energy sources entails several challenges to the operation of the electrical system. As an example, 17th of January of 2018 was randomly chosen in order to analyze its load diagram of total electricity consumption, with the main goal of demonstrating the variability of wind energy. Considering the analysis of figure 1.3, adapted from [6], it is easy to notice that renewable energies have played a significant part in the energy supply along with coal and natural gas.

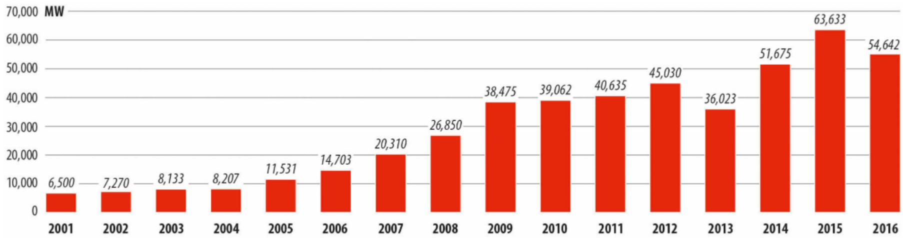

Figure 1.1: Installed wind power

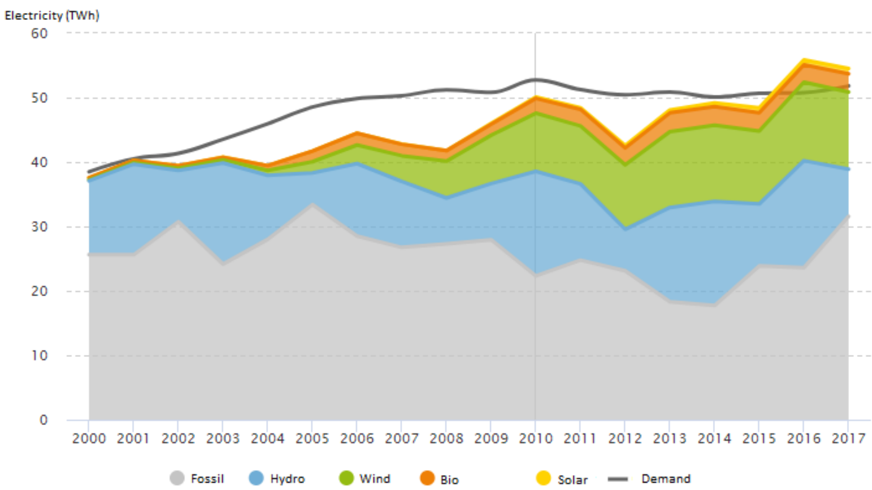

Figure 1.2: Evolution of Power produced from different sources

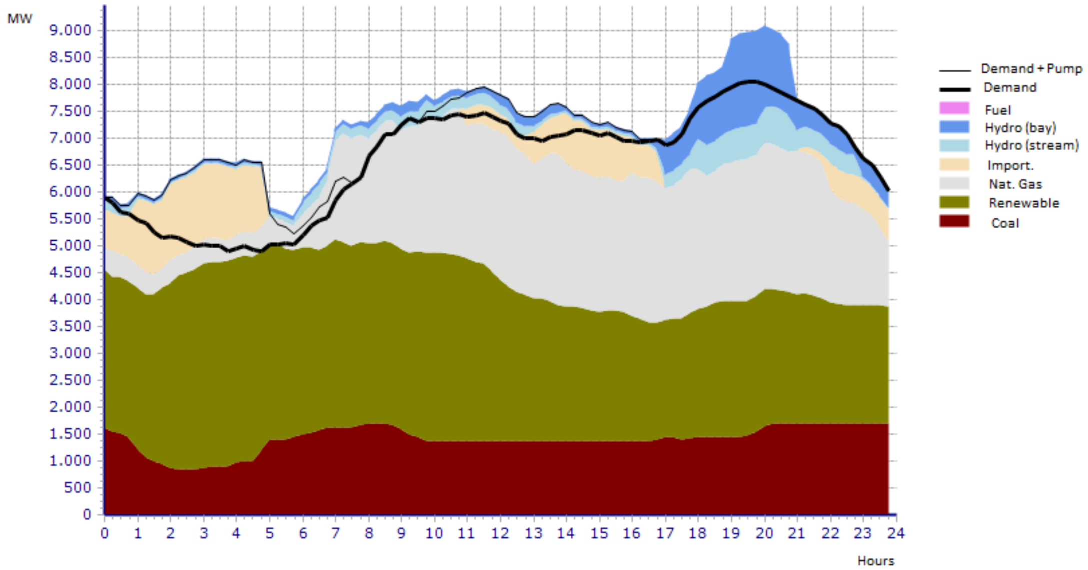

Figure 1.3: Daily Statistics of 17-01-2018

Analyzing figure 1.4, also adapted from [6] which is related only to wind production, it is verified that during the day, the production significantly changed, with a difference of about 1800MW between the maximum and minimum value of production, which reinforces the idea of variability of this type of generation. In the case of the Portuguese electricity system, during periods of low wind production, hydroelectric plants, allow to rapidly cover th lack or decrease of wind power, as can be seen in figure 1.3. As it can be seen, the hydroelectric peak of production is from five to ten, which corresponds to the time period where wind generation is lower.

It can also be seen that on one hand, in some hours of the peak of wind power production compensation through pumping was needed, and consequent import of energy from Spain. Import was also needed in the low-load period of wind power as it can be seen in 1.5. On the other hand, while the wind resource was abundant, some export to Spain occurred.

Taking into account all the uncertainty and variability of renewable energies and the increase in renewable integration in larger electrical the ISO faces an increasing amount of challenges in managing the electrical network. In this way, the increase in operational flexibility is considered a solution to mitigate these problems, allowing secure operation of the electrical system.

In order to achieve the objective of greater flexibility, it is essential to provide the grid with more advanced technologies, changing the traditional electrical system such as:

Network reinforcement and existence of faster production groups in order to ensure the continuity of energy supply, in accordance with the demand [7]. The concept of vehicle-to-grid in the scope of electric mobility can be considered as a significant contribution to the mitigation of climate change and to the air quality of cities [8]. Still the storage of electric energy is considered very important to ensure the flexibility of energy systems.

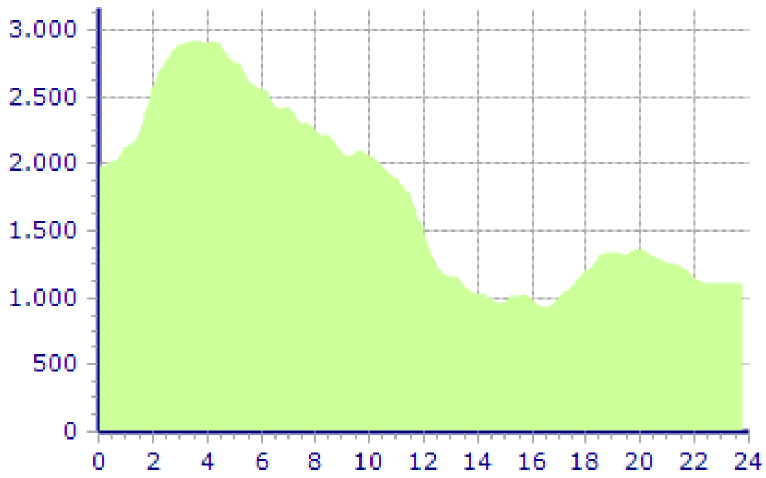

Figure 1.4: Wind Production in 17-01-2018

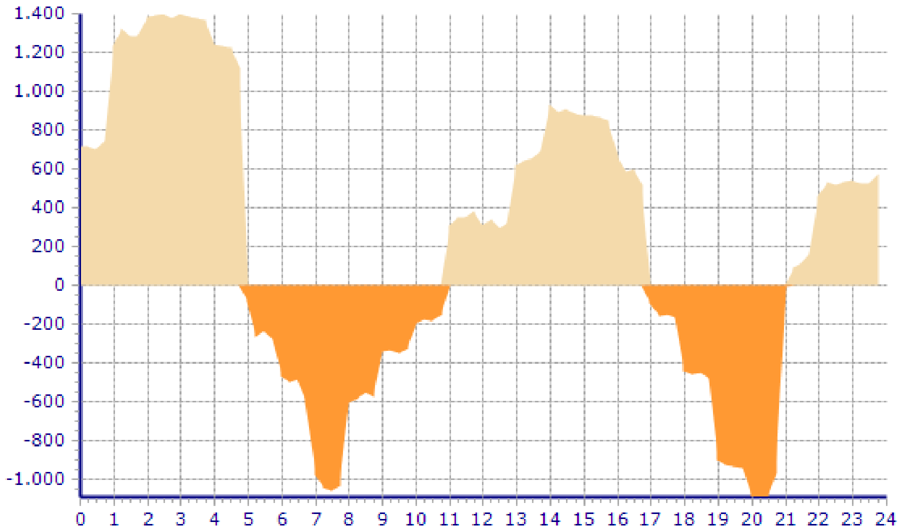

Figure 1.5: Import and Export of Energy in 17-01-2018

The ability to transform the excess electrical energy into another form of energy, such as example in mechanical or thermal energy, which is stored and then converted into electricity, being injected into the network [9]. These are all examples of changes that when and if implemented can help increase the systems flexibility.

To make electrical systems more flexible, electrical networks will have to evolve into Smart Grids through the implementation of innovative concepts, such as Demand Response programs where customer the can play an important role in the system [10].

The concept of DR then requires the installation of new technologies such as smart meters that allow the communication of data in a bidirectional and remote way. In this way, consumers using this new tools to support their process of decision making an contribute for the optimization of the system [11],[12].

From this perspective, international experiences and results about the application of DR where analyzed and it was observed that DRPs can be effectively recognized as possible solutions in the direction of a more flexible electrical network [13].

As mentioned before, the uncertainty of these resources has been already well discussed however, Variability, is currently under investigation due to the increasing flexibility challenges caused by ascending penetration rate of nondispatchable RES in future power systems. Flexibility is defined as the ability of a system to deploy its resources and to respond to changes in the net load. With this in mind some wholesale markets have commenced new activities to meet their required flexibility such as increasing reserve capacity margins, starting fast response units, and withholding some generation capacity. In this regard, one of the promising market renovations has been realized by defining new energy and reserve market mechanisms presented as "flexiramp" in California ISO [14].

1.2 Motivation

Despite the countless benefits associated to renewable energies, this type of energy production comes with a series of problems and challenges when it comes to its integration in the electricity system. The biggest challenges related to system management are regarding wind power and its stochastic and unpredictable nature, which makes it really difficult to predict. One step to helping the Independent System Operator (ISO) solve this challenges is by increasing the systems flexibility, which can be achieved through the implementation of a flexible ramp market, or by an active participation of the consumers through an ideal set of Demand Response Programs (DRPs).

However, in order to implement these solutions, it is necessary to implement changes to the grid, and make them endowed with a bigger technological level, smart grids. It is then in the sense of improving the energetic efficiency of the system that this thesis seeks to work on, by increasing the system flexibility. The increase of renewable energies penetration and the possibility of modeling both the demand and the production, allows an increase in sustainability and reduction in electricity tariffs. However to deal with winds uncertainty it is necessary to utilize methods which make it possible to solve this kind of problems, as well as new and innovative methods which allow the model to optimize different conflicting objectives, the operation cost, and the emissions.

1.3 Goals

To deal with high variability of stochastic market operations and with the aim of assuring a feasible and economic operation under high renewable energy sources penetration, in this work a flexible ramp market is modeled in order to cope with sudden variations and guarantee the rampability of reserve capacity provided by a generation portfolio. On this basis, an integrated stochastic day-ahead market clearing model has been developed to solve the energy, reserve and flexible ramp scheduling considering a real-time power balance problem, and demand changes. The main objectives of this work are summarized as follows:

- To model the flexible ramp market considering the variations of both wind generation and demand;
- To optimize DR programs for providing the required flexibility in handling the variability of the net load in stochastic power systems.

1.4 Structure

This thesis is divided to five chapters, summarized as follows. Chapter 1 corresponds to a general overview where the framework, motivation, goals and used tools are presented.
Chapter 2 presents a literature review on which the Demand Response and flexiramp themes are approached. The main objectives, different types of clients and benefits of DRPs are presented. Also, the flexiramp model and its need is studied. Finally, some stochastic programming and multi objective optimization methods are presented.
Next, in Chapter 3, the problems mathematical formulation is presented, including DR and FR models, the network and its restrictions and all the problems constraints.
Chapter 4 is composed by the numerical studies, where each of the six different case's results are presented and a comparative analysis is carried out afterwards.
Finally in Chapter 5, the main conclusions, proposals for future work and contributions are presented.

1.5 Information and used tools

The work developed for this thesis, had the goal to model the flexible ramp market considering the variations of both wind generation and demand at the same time it optimized DR programs for providing the required flexibility in handling the variability of the net load in stochastic power systems. In order to achieve these, some mathematical simulation models were developed.

In order to solve these problems a model was created using the program, General Algebric Modeling System (GAMS), and the results obtained were treated using Microsoft Excel.

Chapter 2

Literature Review

Global electricity demand is rapidly increasing as rich countries continue to expand, and developing ones grow even faster [15]. The greatest challenges to ensure this ever growing global energy supply relate to energy supply security, price volatility, and sustainability. The primary cause of these problems is the predominant share of fossil fuels in the supply mix.

Moreover, if reliance on fossil fuels is to be reduced, it is necessary to diversify the energy supply portfolio towards cleaner and more sustainable sources of energy, particularly Renewable Energy (RE) [16].

Although most RE sources have exhibited strong growth in terms of installed capacity in the recent years, the deployment of wind power has significantly outpaced other RE sources as the global installed wind generation capacity increased from 10 MW in 1980 to 282 GW by the end of 2012 [17].

Wind power can provide environmental and economic benefits when its proportion of demand is small, but financial costs rise rapidly and environmental benefits fall dramatically as its proportion of demand increases. Wind power is a non dispatchable and highly intermittent electricity source that induces large variability on existent system generators when wind is introduced [18].

In attempting to balance the demand that is unmet by wind, existing generators will ramp up and down more often and operate more frequently at a reduced capacity, thereby lowering average capacity factors and average operating efficiencies. The need to ramp existing generators up and down to follow wind is a particular problem, with generating mixes that have fast-ramping generators better able to integrate wind [15].

Clearly, wind power integration has always been a key research area due to the green future power system target. However, the intermittent nature of wind power may impose some technical and economic challenges to Independent System Operators [19].

In such a situation, increasing operational flexibility is a key solution for mitigating wind power variability and enabling secure operation of power systems. Flexibility should be evaluated from technical, economic, and environmental points of view. Technically, flexibility is required to maintain continuous services in the face of rapid and large fluctuations in both supply and demand sides [20].

Economically, additional cost to provide additional required flexibility should be kept within a plausible range. Moreover, from environmental perspective, lack of flexibility can lead to significant waste of wind generation in the form of wind power curtailment by system operators. However, by obtaining more flexibility from existing conventional units has significant wear-and-tear impacts on existing thermal units and can potentially decrease their expected lifetimes [21].

In this sense, the term flexibility can then be defined as the ability of a power system to cope with variability and uncertainty in both generation and demand, while maintaining a satisfactory level of reliability at a reasonable cost, over different time horizons [22].

2.1 Demand Response Programs

Following the path of increasing flexibility new concepts have emerged, such as Demand And Response (DR) which 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" [23].

Developing information and communication technologies on one hand, and growing the environmental concerns on the other hand cause that DR provides various opportunities for future systems. Due to benefits of DR to attain reliable and efficient electricity markets, Demand Response Programs (DRPs) are a key element on the smart grid path [24].

Beyond the broad improvements in market efficiency and market linkages, demand response creates multiple, specific benefits for market participants and for the general efficiency and operation of electricity markets. To achieve the above benefit, ISO considers different strategies for reduction of load during system peak, reduction of energy consumption, improvement of system load factor and reduction of distance between peak and valley [25].

At the same time DR is known as a powerful measure that has potential to facilitate grid integration of wind power as DR can motivate consumers to increase their consumption when there is an extra amount of wind generation and at the same time DR programs can encourage consumers to decrease their load when the wind power output is low. This rationale mechanism reshapes the load profile of the system and results in a flatter net load and potentially reduces the need for up and down ramping services [26]. These type of programs can be divided in two groups which consequently are divided into smaller sub-groups as shown in figure 2.1 adapted from [19].

2.1.1 Price Based Demand Response Programs

The category of Price Based Demand Response Programs (PBDRP's) includes several programs as seen above, such as real-time pricing (RTP), critical-peak pricing (CPP) and time-of-use (TOU) tariffs and gives customers time-varying rates that reflect the value and cost of electricity in different time periods. If the price differentials between hours or time periods are significant, customers adjust the timing of their flexible loads in order to take advantage of lower price periods.

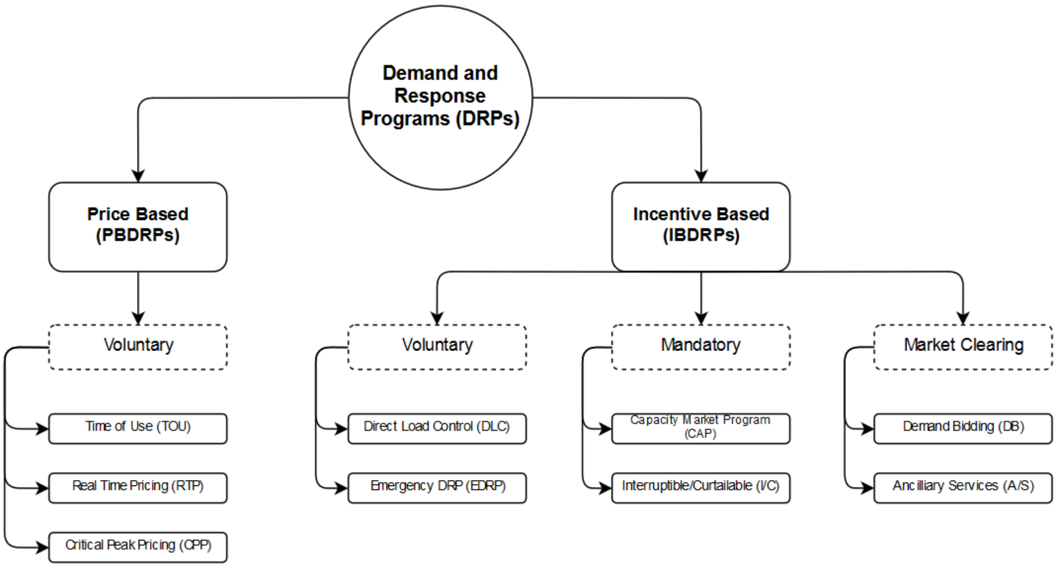

Figure 2.1: Different types of Demand Response Programs

Consequently, from utility's point of view significant peak shaving can be achieved[23]. It can be said that the objective of this programs is to persuade the end-use customers to decrease or shift their demand by changing the electricity tariffs[19].

Focusing now on each of the programs, it can be said that TOU rates establish two or more daily periods that reflect hours when the system load is higher (peak) or lower (offpeak), and charge a higher rate during peak hours. On other words, a rate with different unit prices for usage during different blocks of time, usually defined for a 24 hour day.

TOU rates reflect the average cost of generating and delivering power during those time periods. Daily pricing blocks might include an on-peak, partial-peak, and off-peak price for non-holiday weekdays, with the on-peak price as the highest price, and the off-peak price as the lowest price.

RTP rates vary continuously during the day, directly reflecting the wholesale price of electricity, as opposed to rate designs such as time-of-use or CPP that are largely based on preset prices. RTP links hourly prices to hourly changes in the day-of (real-time) or day-ahead cost of power.

CPP is an overlay on either TOU or flat pricing. CPP uses real-time prices at times of extreme system peak [27]. CPP rates are a hybrid of the TOU and RTP design. The basic rate structure is TOU. However, provision is made for replacing the normal peak price with a much higher CPP event price under specified trigger conditions (e.g., when system reliability is compromised or supply prices are very high) [28].

In figure 2.2 adapted from [29] it is possible to see, respectively:

- TOU's fixed electricity prices for different time blocks within a time period;
- RTP's hourly rate depending on the day ahead real-time price of electricity;
- CPP's high electricity price periods for certain (fixed) days of time within a year.

In order to represent the customer's sensitivity to change in electricity tariffs, PBDRP's use the concept of elasticity of demand, which can be defined as the load's reaction to the electricity price. As the elasticity increases, the load sensitivity to price increases as well. In fact, the elasticity is used to estimate the load reduction and load recovery by DR participants. Actually, demand can react to change in electricity tariffs in one of followings [19].

- A set of loads is reduced without recovering it later, the so-called fixed loads. Such loads have sensitivity just in a single period and it is called "self-elasticity". This value is always negative.
- Some loads could be moved from the peak periods to off-peak periods as required, namely transferable loads. Such behavior is called multi period sensitivity and it is evaluated by "cross-elasticity". This value is always positive.

2.1.2 Incentive Based Demand Response Programs

Incentive-based Demand Response Programs (IBDRPs) main objective is also to encourage customers to change their typical demand in return for a specified incentive payment.

Unlike PBDRPs, implementation of Emergency Demand Response Program (EDRP) imposes some cost to the ISO. This cost is related to the incentive payments to customers for their load reduction in specific hours [19].

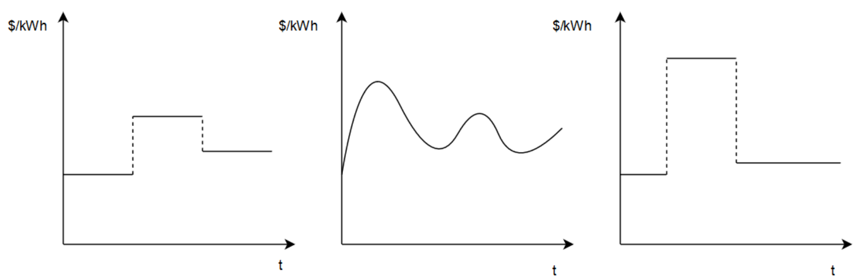

Figure 2.2: Example of tariffs for different PBDRP's

As seen before, Incentive-based programs include;

- Direct Load Control (DLC);
- Emergency Demand Response Program (EDRP);
- Capacity Market Program (CAP);
- Interruptible/Curtailable (I/C) service;
- Demand Bidding (DB);
- Ancillary Service (A/S) program.

The aforementioned programs can be classified into three main subgroups namely: voluntary, mandatory and market clearing programs.

DLC and EDRP are voluntary programs which mean that if customers do not curtail consumption, they are not penalized. I/C and CAP are mandatory programs and enrolled customers are subject to penalties if they do not curtail consumption when directed. DB and A/S are market clearing programs, where large customers are encouraged to offer or to provide load reductions at a price at which they are willing to be curtailed, or to identify how much load they would be willing to curtail at posted prices [30].

Analyzing each of them in bigger detail it is understood that; DLC refers to a program in which a utility or system operator remotely shuts down or cycles a customer's electrical equipment on short notice to address system or local reliability contingencies in exchange for an incentive payment or bill credit. It is also known that these programs are primarily offered to residential or small commercial customers [31].

Based on historical demand, price data, and short term load forecasting, ISO tries to reduce peak demand. The ISO tries to prevent occurring spike prices, by running the EDRP. Large consumers that like to reduce or cut a portion of their consumption, based on ISO announcements, will participate in this program. The ISO will pay them a significant amount of money (almost 10 times of the electricity price in the off peak period) as an incentive [32].

I/C is based on curtailment options integrated into retail tariffs that provide a rate discount or bill credit by agreeing to reduce load during system contingencies and includes penalties for contractual response failures. These programs are traditionally offered to larger industrial customers; On the other hand in CAP, customers offer load curtailment as system capacity to replace conventional generation or delivery resources [31].

Lastly DB program encourages large customers to offer load reductions at a price at which they are willing to be curtailed, or to identify how much load they would be willing to curtail at posted prices. A/S program allows customers to bid load curtailments in ISO markets as operating reserves. If their bids are accepted, they are paid the market price for committing to be on standby. If their load curtailments are needed, they are called by ISO, and may be paid the spot market electricity price [30].

2.1.3 DR types of clients

Two classes of entities, customers and DRPs, may interact with the ISO for the purposes of DR according to the smart grid conceptual model. According to the amount of the consumption within their facilities, customers can be divided into the following classes [31, 33, 34]:

- Large Commercial and Industrial customers who typically have within their facilities the most advanced technologies for controlling the loads (typically related to manufacturing and process control for industrial customers) and may, consequently, participate in either wholesale or retail electricity markets. Inside commercial facilities, instead, the main loads are normally those used for the management of the facilities, such as heating, ventilation and air-conditioning (HVAC) systems and lighting.

  Most industrial customers and certain large commercial customers, having on site generation equipment either for emergency backup or for auxiliary power, may use this kind of generation for DR. Besides, some industrial facilities, such as pulp and paper manufacturing, have autonomous, discrete, production processes that, in case of necessity, can be shifted to other times of the day or to different days.

- Small Commercial and Industrial customers which are diverse and, in some cases, seem more like residential customers while in others cases look more like large Commercial and Industrial customers. PEVs represent an important new load on existing distribution systems and their diffusion will support load-shifting. Nevertheless, distribution systems should be correctly reinforced in order to avoid that their usage in DR programs may determine voltage problems, a degradation of the power quality and even probable damage to utility and consumer equipment.

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- Residential customers which are characterized by relatively small and somewhat limited types of loads and are not actually motivated to invest much in order to manage their electrical usage. They usually only take part in retail electricity markets and mainly participate in direct load control programs. This is likely to change in the near future, thanks to the deployment of new standards and technologies such as advanced metering infrastructure (AMI), which permits lower-cost equipment in the marketplace. New standards and technologies for building automation systems will also allow smart homes providing technical support to the SGs.

In order to be able to use the various DRPs, it is necessary to equip the networks with more advanced technologies, allowing an active control of the loads. This is the only way to reduce or shift loads for more favorable periods. Intelligent networks allow bi-directional control and communication through new smart meters.

These meters provide access to a greater amount of information compared to traditional counters. They also ensure, in real time, the reading and dissemination of consumption and the exchange of information with ISO. In this way, consumers have access to energy prices and can make more informed decisions, contributing to an increase in energy efficiency[35]. The figure 2.3, based on [35], shows how a smart meter works.

2.1.4 DR customer behavior

Changes in human behavior are believed to be needed because physical and technical innovations imply changes as individuals need to accept and understand them, buy them, and use them in proper ways [36].

On one hand, in the beginnings of the deregulation, customers usually had no effective participation in the power markets, and Independent Power Producers (IPP), Regional Transmission Organizations (RTO) and Regulatory Bodies have been the most effective entities in the markets. Therefore, customers were isolated from the benefits and the information of the markets. They did not have enough knowledge and hardware to participate effectively in the markets.

On the other hand, many customers prefer to be isolated from the price fluctuations and the risks in the volatile power markets. This kind of customers' behavior and their absence in the electricity markets, caused spike prices and congestion in the transmission lines [37].

Price elasticity is a normalized (for the relative price change) measure of the intensity of how usage of a commodity (in this case electricity) changes when its price changes by one percent. It facilitates a comparison of the intensity of load changes among customers since the price change has been factored out; the price elasticity is a relative measure of the customers' response. Figure 2.4, adapted from [38] shows how the demand elasticity could significantly affect electric price . It can be seen that "demand curve 1" tends to "demand curve 2" as the demand-price elasticity increases.

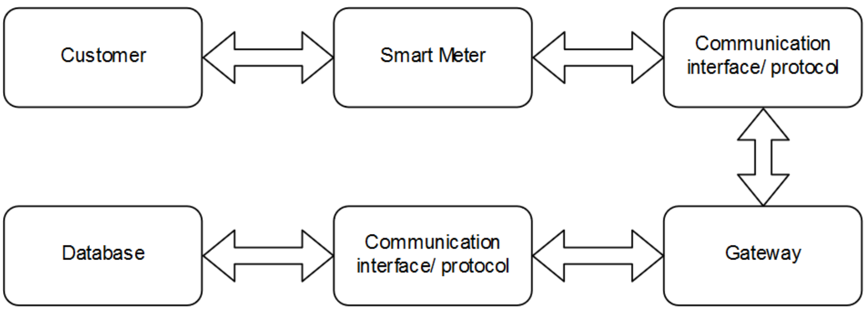

Figure 2.3: Metering architectures of a smart meter

Indeed bigger price elasticity will lead to lower marketing clearing price. As shown in figure 2.4, a small reduction of demand in peak periods will result in a big reduction of the electricity price [38].

The IBDRPs, which are usually voluntarily and encourage customers to participate, can be named as reward wise programs. On the other hand implementing PBDRP increases the utility's revenue as customers pay more for their electricity consumption during peak hours. PBDRPs are often mandatory and hence can be named as punishment wise programs.

The model differs between the impacts of incentive-based (reward-wise) and price-based (punishment wise) programs on customer's response. It was concluded that IBDRPs could lead to customers habit formation if there is enough educational and publicity measures. The impact of implementing each of these is very different as rewards may lead to more significant improvements and usually lasts more [23].

2.1.5 DR benefits

Depending on the target, design and performance, as well as on other factors, such as the utilized enabling technologies and the structure of the system, DR may offer a broad range of potential benefits on system operation and expansion and on market efficiency. The benefits of DR can be classified into terms of whether they accrue directly to participants or to some or all groups of electricity consumers as follows:

- Participant bill savings: electricity bill savings and incentive payments the customer receives for agreeing to modify load in response to current supply costs or other incentives.

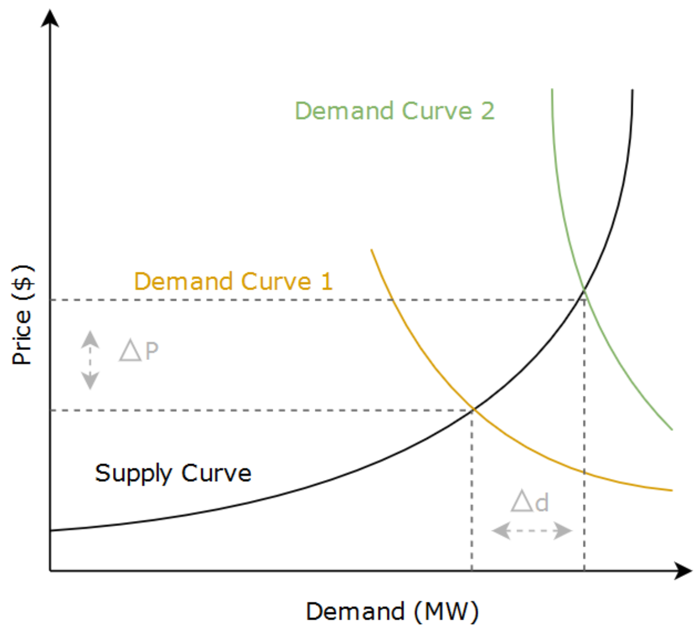

Figure 2.4: Price elasticity

- Bills savings for other customers: lower wholesale market prices that result from using less energy when prices are high, or from shifting usage to lower-priced hours.

- Reliability benefits: refer to customers' benefits perceived from reduced probability of being involuntarily curtailed and incurring even higher financial costs and inconvenience, or to societal benefits according to which the customer is gratified from helping avoiding extensive shortages.

- Market performance: DR prevents the exercise of market power by electric power producers.

- Improved choice: customers have more options for electricity costs management.

- System security: system operators are endowed with more flexible means to meet contingencies.

These benefits can be also categorized according to the activity of power systems where they originate as shown in tables 2.1, 2.2 and 2.3 adapted from [31] and described in the following [31], [39], [40], [41].

Table 2.1: Operation Benefits

	Operation
Transmission and Distribution	Relieve congestion manage contingencies, avoid outages Reduce overall losses Facilitate technical operation
Generation	Reduce energy generation in peak times Facilitate balance of supply and demand Reduce operating reserver requirements or increase short-term reliability of supply
Demand	Consumers more aware of cost and consumption, and even environmental impacts Give consumers more options to maximize their utility: reduce electricity bills or receive payments

Table 2.2: Expansion benefits

	Expansion
Transmission and Distribution	Defer investment in network reinforcement or increase long-term network reliability
Generation	Avoid investment in peaking units Reduce capacity reserves requirements or increase long-term reliability of supply
Retailing	Allow more penetration of intermittent renewable sources
Demand	Take investment decisions with greater awareness of consumption and cost

Table 2.3: Market benefits

	Market
Retailing	Reduce risk of imbalances Reduce price volatility New products, more consumer choice
Demand	Increase demand elasticity

2.1.6 Energy Markets with integrated renewable energies and DR

In the past, the electricity industry was organized as vertically integrated monopolies that were sometimes also state-owned. The growing ideological and political disaffection about vertically integrated monopolies and the liberalization successes in other network industries have led to liberalization initiatives worldwide in the electricity industry.

In a liberalized market, the reliable electricity that consumers take for granted is the result of a bundle of tasks performed and services provided by different players. Well-functioning markets are therefore a critical success factor of the liberalization.

The process of deregulation of the electric sector has emerged with the objective of improving market uncertainties, such as the price variation availability of producers and variation in demand. It was through this that a change occurred in the organization and management of energy systems, giving rise to de-verticalization of the sector and the transformation of a monopoly market into a competitive one [42].

With the global change where the world is moving from a centralized operational approach to a competitive one, the understanding of electric power supply as a public service is being replaced by the notion that a competitive market is a more appropriate mechanism to supply energy to consumers with high reliability and low cost.

An electricity market usually includes two instruments to facilitate trade among power producers and consumers: the pool, which is an e-commerce marketplace, and a framework to enable physical bilateral contracts. Financial contracts to hedge against risk of price volatility are possible and advisable, but they do not affect the physical operation of the system.

In this way, in today's electric energy market, it is possible to participate in two different ways. On one hand there are Bilateral Contracts in which two parties, supplier and buyer of energy, mutually agree on the details (price, quantity, quality) of a transaction whose payment and delivery of the energy will only be made at a future date. That is, the agreement is made in advance, the price being fixed at that time and consequently not subject to variations [43].

On the other hand, there is the Electric Pool in which the ISO determines the optimal dispatch for each hour or half an hour for the next day, resulting from agreements between the purchase offers and the sale offers. Within the Power Pool, there are two distinct moments of energy trading: the day-ahead market and the balance market where several sellers and buyers participate.

In both markets, energy suppliers make their consumers submit their purchase proposals. The system operator combines both proposals and constructs aggregate sales and purchase curves. The intersection of these same curves originates the marginal price of the system that corresponds to the value paid for the energy traded.

What distinguishes the day-ahead market from the equilibrium market is the time when each occurs, the next day's market happens one day before the delivery of energy while the Equilibrium Market happens a few minutes before the delivery of energy (real time), with the main objective of keeping the system in constant balance with the appropriate levels of quality and safety. The Equilibrium Market corresponds to the last opportunity to balance production and consumption [44].

With the integration of renewable energies into the electric energy markets and the potential increased flexibility of the system, causes a transition in the approach of this type of problems to occur. Since the production of renewable energies is very dependent on weather conditions, the generation of energy from this type of generation becomes uncertain and difficult to to predict. For this reason, occurs the transition from deterministic approaches to stochastic nature [45].

In addition, unlike conventional units, this kind of generation is characterized by non dispatchability and for this reason it is necessary to resort to predictions to schedule the units that will provide the power. However, renewable energy has priority over conventional units since the price is lower. Once again, stochastic approaches are needed to deal with the characteristic uncertainty of renewables, since deterministic approaches are only useful when the amount of energy for the next day is known.

In this type of stochastic approaches some optimization models are used, such as SCUC, as they facilitate the process of decision making in the scheduling and dispatch of the electric resources.

In addition to being able to deal with the uncertainty associated with renewable energies, they are also able to manage the variations on the demand side and the failures of the system components [46], [47].

In fact, the production of energy from renewable sources such as wind energy is preferable to conventional units, however in order to achieve a continuous power supply, without interruptions, it is necessary to use this type of conventional generators. These generators are required in order to maintain system security and safeguard the system against fluctuations during the actual operating time of the system. To achieve these objectives, it is necessary to request a significant amount of energy in advance, called reserve [48].

The purpose of the reserve is to compensate for production deviations and variations in electricity consumption, in order to maintain continuity of service and avoid disturbances of the system.The acquisition and scheduling of the reserve implies that the system operates at a level lower than its maximum capacity, while its use translates usually into a re-dispatch of units previously engaged in the day market voltage cut-off and / or the rapid start-up of extra to cover the faults in the delivery in real time. In figure 2.5 is represented an adaption from [44] of the electrical market.

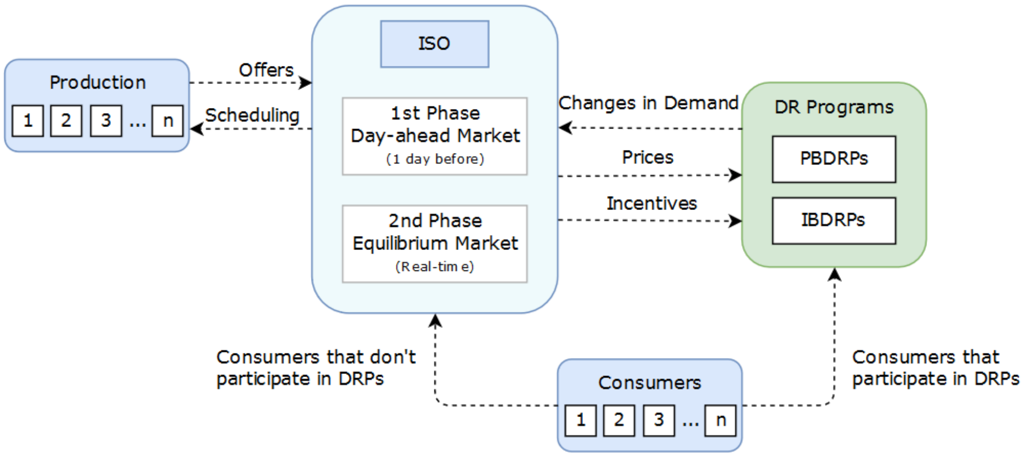

Figure 2.5: Electrical Market

2.2 Flexible Ramp

Deployment of Renewable Energy Sources (RES) is expected to increase the variability in power system operations. Higher variability in stochastic market operations, especially caused by higher penetrations of RES, would require greater flexibility to maintain the power supply balance [49].

Flexibility is the ability of a system to use its resources to meet changes in the net load, and so is considerably different from the capacity adequacy of a system. While the latter is a function of the amount of capacity available, the forced outage rate of each resource and the system demand, system flexibility is affected by many additional factors, such as the generation portfolio, the availability and ramp rate of resources, the magnitude and frequency of net load ramps, the predictability of net load variations, interconnection to other systems, the presence of energy storage, demand side resources, the market arrangements in place and reserve provision strategies [50].

Some wholesale markets have commenced new activities to meet their required flexibility such as increasing reserve capacity margins, starting fast response units, and withholding some generation capacity. In this regard, one of the promising market renovations has been realized by defining new energy and reserve market mechanisms presented as "flexiramp" in California ISO. Among various possible aspects, day-ahead resource scheduling to procure adequate ramping capabilities is the main motivation of the present work [14].

As the variability increases, the balance of supply is potentially maintained in power system operations by fast-ramp thermal units. Controllable thermal resources are poised for following the fluctuations in net loads (total load minus local RES generation) [51].

However, unexpected deviations from the expected net load or high rates of change in net loads beyond the scheduled dispatch may leave dispatchable generating units with sufficient residual capacity but insufficient ramping capability, which could lead to short-term scarcity events in electricity markets. Flexible ramping capability is demonstrated by the operating reserves (spinning or quick-start) for ramping between consecutive dispatch intervals. Sufficient flexible ramping capability, as a novel requirement for power system operations, would be capable of coping with uncertainties in net load quantities [49].

In restructured electric power systems, DR becomes more appealing as fuel prices increase and the quest for higher reliability becomes more prevalent. In developing the day-ahead schedule, the hourly unit commitment (UC) has conventionally adopted a stepwise output of thermal generating units as well as fixed ramp-rate limits for representing generator rotor fatigues as the hourly system demand is changed [52].

It is perceived that the ramping up/down of generating units will not adversely affect the life of a generator rotor shaft as long as the incremental generation dispatch in two consecutive periods is limited to a preselected value. However, ramp-rate limits could constrain the independent system operator (ISO)'s flexibility to select appropriate generation levels at different operating hours. A serious conflict could potentially arise in power system operations when the day-ahead hourly schedule cannot be realized based on limited ramp-rates of generators in real-time [53].

To deal with high variability of stochastic market operations and with the aim of assuring a feasible and economic operation under high renewable energy sources penetration, there are two applicable solutions [54]:

- the incorporation into the electricity market of emerging flexible resources, including Demand Response (DR), Bulk Energy Storages (BESs) and Plug-in Electric Vehicle Parking Lots (PEV PLs) considering their own specific characteristics;

- new flexible ramp market that can cope with sudden variations and guarantee the rampability of reserve capacity provided by a generation portfolio.

2.2.1 New flexible ramping constraint in real-time

Flexiramp can be defined as the capacity in a time interval to meet higher or lower than expected net energy demands in subsequent intervals, at which time that capacity can be optimally dispatched to meet those energy demands. Flexiramp differs from spinning and other operating reserves in two ways.

One is that spin is often or usually reserved for specified contingencies (such as line or plant outages), and according to the business practices manual in most ISOs, spin cannot be used just to meet unexpectedly high net load arising from unexpected wind/solar turn down or demand increases. In contrast, flexiramp capacity is reserved (and paid for) in one period to meet possible ramps in the next period, and can be dispatched on an economic basis to meet that next period's load.

This difference means that flexiramp will be called on much more often to produce energy than traditional operating reserves. Therefore it is important to consider the cost of calling on the reserves for energy.

The second difference is that flexiramp is reserved, and paid for, in an interval before its possible use for energy, whereas spin, regulation, and other operating reserves are reserved and settled in the same interval in which they might be used. The major reason for reserving (and paying for) flexiramp ahead of the time of possible use is that low cost capacity might be held back in one interval to provide ramp capability for later intervals, thus incurring an opportunity cost in the first interval. However, without a flexiramp payment, there is no guarantee that a generator incurring such an opportunity cost would be compensated by extra energy revenue in later intervals, unless the extreme ramp event it was reserved for actually occurs [55].

The CAISO flexiramp markets also share some characteristics with the MISO ramp capability. For instance, in both markets, ramp is acquired system-wide rather than zonally. The market price paid to providers is based on the shadow price (dual or Lagrangian multiplier) of the ramp capability/flexiramp constraint in the market software, which simultaneously optimizes energy, ancillary services, as well as ramp.

Up- and down-ramping ability are separate constraints with separate prices. Generators do not provide price bids for ramp, so prices are based just on the marginal opportunity cost of diverting capacity from energy or ancillary services in order to meet the ramp requirements [56].

This new constraint is necessary to address certain reliability and operational issues observed in the ISO's operation of the grid. In certain situations, reserves and regulation service lack sufficient ramping capability and flexibility to meet conditions in the five minute market interval during which conditions may have changed from the assumptions made during the prior procurement procedures.

These instances pose reliability concerns because the ISO must re-dispatch resources in real time and there is insufficient committed resource flexibility the ISO may be drawing on operating reserves, regulation or on the interconnection.

This issue can be addressed in part by the adoption of this flexible ramping constraint, which is designed to ensure that sufficient upward and downward (enforcing downward ramping constraint may not be effective in times of over-supply conditions as commitment of additional resources to be able to ramp down may exacerbate over-supply conditions) ramping capability of dispatchable resources is committed to enable the real time dispatch to follow loads efficiently and reliably over an estimated range of potential variability of net load around the forecast.

Under the flexible ramping constraint, the RTPD unit commitment and real time dispatch will ensure the availability of a pre-specified quantity of upward and downward five-minute dispatch capability on committed flexible resources, from such capacity not designated to provide regulation or contingency reserves (spinning and non-spinning reserves) and the upward capacity not utilized to meet the load forecast. The ISO will monitor the effectiveness of this new constraint and may in the future consider applying it in the day-ahead market.

Moreover, the flexible ramping constraint utilizes an operator-specified quantity of upward and downward five-minute ramping capability and affects the RTPD unit commitment and the RTD dispatch for intervals beyond the binding dispatch interval so as to provide for the availability of this capacity dispatch in the RTD. The flexible dispatch capability will come from capacity that is not designated to provide regulation or contingency reserve and will not offset the required procurement of those reserves. This capacity will be available for five-minute dispatch instructions from the RTD, and if dispatched above minimum load will be eligible to set real-time LMP prices subject to other eligibility provisions established in the ISO tariff.

This constraint will provide the online dispatch flexibility to follow the net load variation efficiently in the event the actual load is higher or lower than forecast or supply is not responding as expected or instructed reducing the need to bias the HASP procurement.

The quantity of flexible dispatch capability will be determined by operators using tools that will estimate [57]:

- Expected level of imbalance variability;
- Uncertainty due to forecast error;
- Differences between the hourly, 15 minute average and actual 5 minute load levels.

2.2.2 Operational need for real-time flexibility

IFM, RTPD and RTD optimize resources based on a single imbalance energy forecast amount for an entire interval (hour, 15 minute or 5 minute period, respectively), assuming a perfect load forecast, generation behaving based on dispatch and constant conditions over the interval. There are times IFM and RTPD optimize resources so efficiently that there is little or no additional on-line available unscheduled capacity for RTD to dispatch for any variation from the constant conditions assumed by IFM and RTPD.

The IFM, especially in the peaks and valleys, can optimize resources to meet the average load forecast for the hour, but these may not necessarily meet the imbalance for every five minutes within the hour. The same happens to RTPD that for the 15 minute period commits or de-commits resources sufficient to meet the load forecast at the time the RTPD is run for a single load forecast but not sufficiently good for RTD to meet changes between the time RTPD is ran and the time RTD runs.

At the same time, running for each 15 minutes may not be sufficient to meet the imbalance energy needs for each 5 minute interval within each 15 minutes. This issue is more prominent when the load is increasing in the morning and evening ramps.

Some reasons for imbalance changes include:

- Changes in load conditions from forecast;
- Differences between average 15 minute imbalance energy needs and 5 minute imbalance energy needs within the 15 minute interval;

- Resources shutting down without sufficient notice;
- Variable energy resources delivering more or less than forecast;
- Contingency events;
- High hydro run-off decreasing resource flexibility;
- Interconnections tagging and delivering less than awarded in HASP;
- Interchange ramp in and out between hours.

When these real-time events occur and available dispatch ramping capability is exhausted, leaning on regulation of the interconnection (biasing the load and/or exceptional dispatch) are the only tools left for the ISO to deal with this issue. Shortages of ramping variability are an existing operational issue as more intermittent renewable resources are integrated into the system [57].

2.2.3 Effect of lack of flexibility

The lack of sufficient operational flexibility to respond to the imbalance variability and the uncertain magnitude of differences between expected conditions in RTPD and RTD results in both operational and market impacts as it can be seen in figure 2.6 adapted from [57].

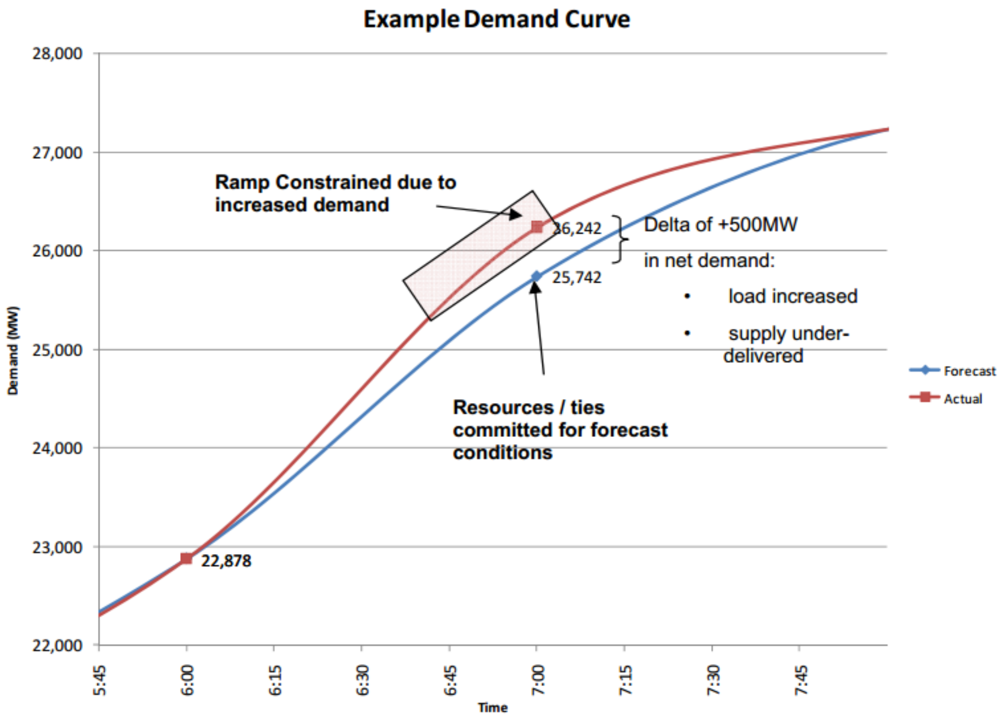

Figure 2.6: Need for flexibility constraint

2.2.4 Impact of Electric Vehicles in Ramp Market

EVs have become more and more popular, not only because of their capability to decrease carbon emission in transportation, but also because of their potentials to improve power system reliability and flexibility. EVs can be quite adjustable in different operation modes:

- grid-to-vehicle (G2V);
- vehicle-to-grid (V2G);
- vehicle-to-building (V2B);

and they have been suggested to participate in the electricity market by providing ancillary services such as reserve and regulation [58]. Taking a deeper look at the impact of the different operation modes it is easy to realize that the most important role for V2G may ultimately be in emerging power markets to support renewable energy.

The two largest renewable sources likely to be widely used in the near future, photovoltaic (PV) and wind turbines, are both intermittent.

At low levels of penetration, the intermittency of renewable energy can be handled by existing mechanisms for managing load and supply fluctuations. However, as renewable energy exceeds 10–30% of the power supply, additional resources are needed to match the fluctuating supply to the already fluctuating load.

Intermittency can be managed either by backup or storage. "Backup" refers to generators that can be turned on to provide power when the renewable source is insufficient. "Storage" has the advantage of additionally being able to absorb excess power, but adds the constraint that giving back power is duration-limited (as is absorbing it). In terms of V2G, backup can be provided by the fueled vehicles (fuel cell and hybrid running motor-generator). Storage can be provided by the battery vehicle and the plug-in hybrid running V2G from its battery [59].

On the other hand, V2B is defined as exporting electrical power from a vehicle battery into a building. It considers batteries in BEVs/PHEVs as a generation resource for the buildings via bidirectional power transfer through energy exchange stations (chargers/dischargers) at certain periods of time, which could increase the flexibility of the electrical distribution system operation. It is expected that V2B operation will improve the reliability of the distribution system, provide extra economic benefits to the vehicle owners, and reduce the home or building electricity purchase cost based on the demand side management (DSM) and outage management (OM) programs with customer incentives [60]. However, the constraints on EV battery capacity and battery cost related to frequent charging/discharging are the core problems restricting EV flexible performance in the electricity market [58].

2.3 Stochastic Programming

In decision-making under uncertainty, the manager has to make optimal decisions over time with incomplete information. On this same horizon, the number of steps of the problem are defined. According to the number of stages, one can distinguish between a two-step or multi-step stochastic programming. With regard to programming in two steps, it is considered that the decision-making is made in two different stages, where there is a stochastic process represented by different scenarios.

In the first step, decisions are made before the stochastic process is carried out, which is to say the variables are not scenario-dependent. While in the second stage of the problem, decisions are made after the stochastic process is carried out. Consequently, the decision is defined for each scenario considered.

The objective function of this type of problem can, for example, correspond to the minimization of the expected costs of operation, that is, to reduce costs related to the dispatch of the energy and reserves made in the day-ahead-market and the expected cost of the bids related to the Equilibrium Market.

These costs are calculated based on energy and reserve offers submitted by participants in the day-ahead-market. The objective function is subject to certain constraints, such as the constraints related to energy dispatch and reserve in the day-ahead-market, restrictive resource balance equations and constraints that state the nonnegative nature of energy and reserve variables .

In [19] a stochastic programming problem is studied in which: the first stage corresponds to the decisions made on the day-ahead-market, this is, the traditional UC problem where conventional units are scheduled along with starting and deceleration costs. It is also at this stage that the amount of wind power to be used is decided and the reservation request made by the system operator.

The second phase corresponds to the last adjustments made in the equilibrium market, where the balance between production and consumption must be ensured. The producers who are characterized by non-dispatchability have to participate in this market in order to cover deviations from production in relation to the market value of the day-ahead-market.

These deviations can be positive or negative. In order to solve these differences one can resort to three possible solutions: activation of the previously requested reserve, reduction of wind power or change in loads for different time periods, always with the aim of equalizing production and consumption.

The main purpose of this type of stochastic programming is to schedule the number of units and DR resources in order to minimize the operational cost of the system, with the integration of large quantities of renewable energy [61], [62], [63].

Furthermore , stochastic unit commitment (SUC) has been introduced as a promising tool to deal with power generation problems involving uncertainties. The idea of SUC is to utilize scenario-based uncertainty representation in the UC formulation. Compared to simply using reserve constraints, stochastic models have certain advantages, such as cost saving and reliability improvement [63]:

- Two-Stage model

  The benefits of using stochastic programming versus deterministic models can be evaluated by two measures in terms of the total expected cost: the expected value of perfect information and the value of stochastic solution. In a two-stage SUC model, decisions are divided into two categories: day-ahead versus real-time decisions.

  Because of the large number of scenarios simulated, the resulting deterministic problem could be quite large. However, in the second stage, different scenarios are not directly linked to each other. Because of this, decomposition has been used as an efficient tool for stochastic unit commitment problems. In the two-stage model, once the first-stage decision is made, the second stage of different scenarios can be treated independently, resulting in a group of much smaller individual optimization problems. In figure 2.7 is represented a scenario tree for a two-stage problem adapted from [63].

- Multi Stage Model

  In contrast to two-stage models, which treat uncertainty statically (only once), multistage models attempt to capture the dynamics of unfolding uncertainties over time and adjust decisions dynamically. To facilitate the formulation of multistage models, scenario trees are often used, as illustrated in figure 2.8. When information is updated hourly (or multihourly or subhourly), decision-makers can adjust their unit commitment, dispatch, and reserve decisions based on the current states of the system and future uncertainties. The main benefit of using multistage models is that the interaction between decision making and uncertainty unfolding is represented more accurately and realistically. Figure 2.8 which represents scenario tree for a multi stage problem adapted from [63].

Multi-step stochastic problems can be used to solve future problems through planning. Usually this type of problem is formulated from the ISO point of view. However, the realization of these problems increases the computational size of the problem, making it often difficult to solve [64].

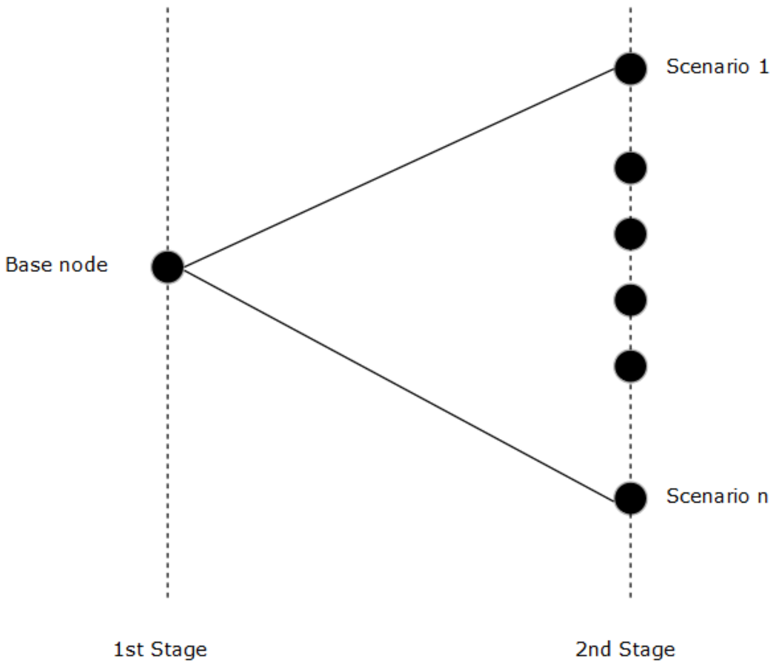

Figure 2.7: Two-stage problem scenario tree

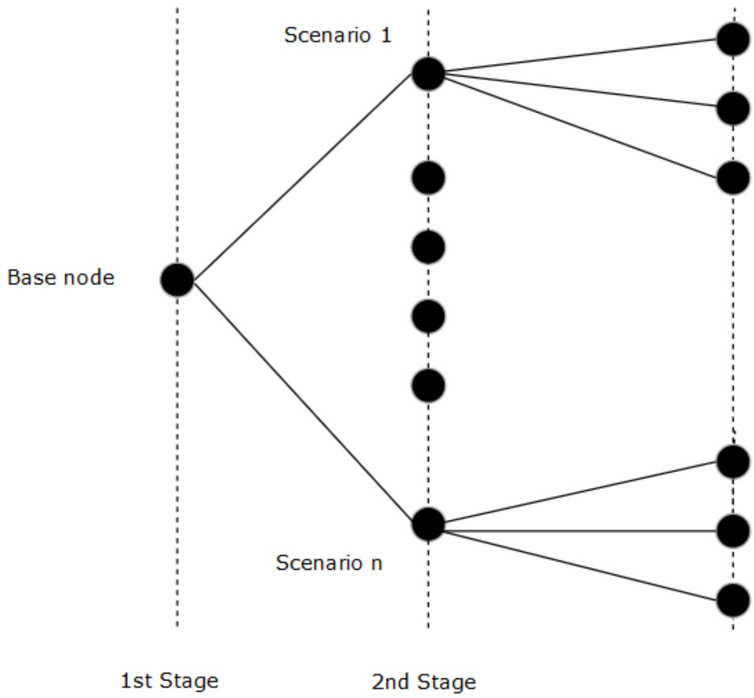

Figure 2.8: Multi stage model scenario tree

2.4 Multi Objective Optimization

Optimization is an essential process in engineering applications. In these areas, sometimes, multiple and conflicting objectives need to be met. Traditionally, the solution to this type of problem is to convert all the objectives into a single objective function. However, the application of this technique has some limitations, such as, prior knowledge of the limits of the functions that are used as constraints and the objective function to have a single solution. Thus it becomes impossible to know all the optimal solutions for all the objectives in simultaneously.

The operation of electrical systems naturally requires multi-objective optimizations. For example, for economic / environmental dispatch, the minimization of operational costs of the system, minimizing losses and minimizing emissions of pollutant gases are some of the of the functions that can be incorporated to create an MO problem. Some other functions with divergent objectives in the transmission networks are the losses, transmission capacity and voltage stability. Other targets in the distribution networks include losses, load factor and voltage stability.

In comparison to problems with only one objective function, MOs are much more difficult to solve, since there is more than one solution.

Rather, there is a set of acceptable solutions that lie within a range of values. This set is called the Pareto front.

The MO optimization is considered as the phase under analysis of the decision making process, and consists of determining all the solutions to the MO problem that are optimal in the Pareto front. The solution chosen, the one most desired for the decision maker, is chosen from the Pareto set. The creation of the Pareto front has several advantages. It allows the decision maker to make a more informed choice by looking at the wide range of solutions. In this way, this feature becomes very useful in the way it provides a better understanding of the system.

In the following figures, adpated from [65] are shown the Pareto curves for the optimization of a bi-objective problem, where the sets of solutions that simultaneously optimize f1 and f2 are presented. Figure 2.9 represents the maximization of the two functions, while figure 2.10 intends to show the most effective solution for the minimization of both functions.

There are different methods of solving an MO problem. One can use the classical methods, which consist of converting the MO problem into a single function by aggregating all objective functions such as the Weighted Aggregation method and Goal Programming or by optimizing one of the functions and treating the others as constraints, like the e-constraint and the Augmented e-constraint.

There are also other algorithms, known as intelligent algorithms, such as genetic and evolutionary algorithms that offer great flexibility to the decision maker, especially in cases where no prior information is available [65], [66], [67].

In short, the main purpose of MO problems is to discover the set of acceptable solutions for various conflicting functions. The solutions are presented to the decision maker through a Pareto curve. Regarding all possible solutions the decision maker chooses the preferred solution, according to his point of view.

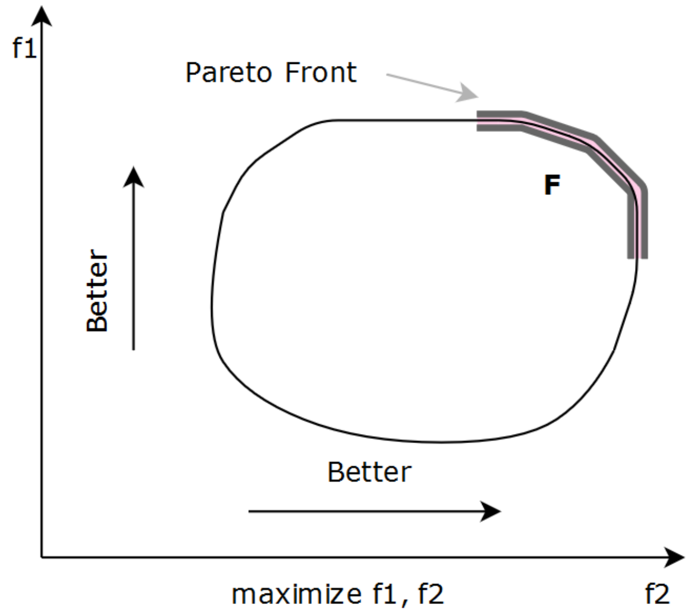

Figure 2.9: Max Pareto

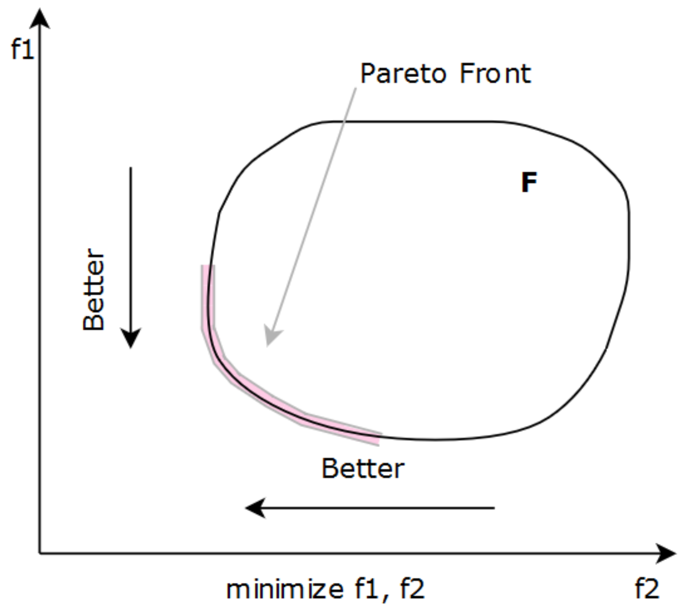

Figure 2.10: Min Pareto

Chapter 3

Mathematical Formulation - Stochastic Multi Objective Problem

3.1 Electricity Market Model

In this section, each participant of the electrical market is modeled as an agent whose main purpose is to maximize its own profits.

In this sense the ISO gives the day-ahead market price using a Security Constraint Unit Commitment (SCUC). The objective function of the proposed problem corresponds to the minimization of the cost to the System Operator, translated by:

$$Min \sum_{t=1}^{T} [(\lambda_{i,t} \cdot P_{i,t}) + inc] \tag{3.1}$$

where, i corresponds to the number of the generation units, $\lambda_{i,t}$ to the price of each generation unit at each hour and $P_{i,t}$ to the power each generation unit (i) is producing in a given hour (t).

The price of each generation unit is calculated using equation 3.2, where A_i and B_i correspond to the linearization of each generation units price curve and $U_{i,t}$, is a binary variable used in the SCUC which indicates if the generation unit is going to be producing ($U_{i,t}$=1) or not ($U_{i,t}$=0).

$$\lambda_{i,t} = P_{i,t} \cdot A_{i,t} + U_{i,t} \cdot B_{i,t} \tag{3.2}$$

Regarding the cost of the incentive paid by the system operator to the clients, this is calculated using equation 3.3.

$$inc = \sum_{t=12}^{T_{peak}} [\Delta d \cdot A \cdot \eta_A] \tag{3.3}$$

where Δd represents the change in load as a result of the application of an incentive based DR program, A is the value of the incentive and η_A corresponds to the weight of the incentive coefficient which makes it possible to distinguish from a IBDRP and a PBDRP.

This is to say, if $\eta_A = 1$, it's a IBDRP and when $\eta_A = 0$, the program presented is a PBDRP. For this case, a PBDRP is used, so η_A is always zero and incentives are not applied.

3.1.1 Constraints

The constraints related with the electricity market model are the following. Equation 3.4 corresponds to the limits of each generation unit at each hour, this is, the production ($P_{i,t}$) of each generator i, at a given hour t, can not be lower than its minimum ($P_{i,t}^{min}$) or higher than its maximum ($P_{i,t}^{max}$). It is also mandatory that the maximum production of the generation units has to be higher than the value of the electrical demand ($d_{i,t}$) and the reserve (R_t^{min}), represented by equation 3.5.

$$P_{i,t}^{min} \cdot U_{i,t} \leq P_{i,t} \leq P_{i,t}^{max} \cdot U_{i,t} \tag{3.4}$$

$$\sum_{i=1}^{i} P_{i,t}^{max} \cdot U_{i,t} \geq \sum_{i=1}^{i} d_{i,t} + R_{i,t} \tag{3.5}$$

Equations 3.6 and 3.7 represent the ramp-up and ramp-down constraints of each generation unit, where RU_i and RD_i represent the ramp-up and ramp-down rates of each generator, respectively.

$$P_{i,t} - P_{i,t-1} \leq RU_i \cdot U_{i,t} + P_i^{min} \cdot (1 - U_{i,t}) \tag{3.6}$$

$$P_{i,t} - P_{i,t-1} \leq RD_i \cdot U_{i,t} + P_i^{min} \cdot (1 - U_{i,t}) \tag{3.7}$$

Equation 3.8 represents the loss of load in line l at a given hour t, which is dependent of the square of the flow in the line $F_{l,t}$, and of the resistance of each line R_l. The sum of the losses of each line gives us the total loss of the system as seen in equation 3.9.

$$Loss_{l,t} = F_{l,t}^2 \cdot R_l \tag{3.8}$$

$$Loss_{total} = \sum_{l} Loss_{l,t} \tag{3.9}$$

3.2 Electrical Grid

For this problem the chosen solution was based on the IEEE 24 bus Reliability Test System, presented in figure 3.1, as it is very similar to real large-scale electrical grids that contain a variety of generation technologies. The six hydroelectric generation units at bus 22 were removed and the final modified grid is then defined with twenty-six generation units, six wind farms, thirty lines and seventeen loads.

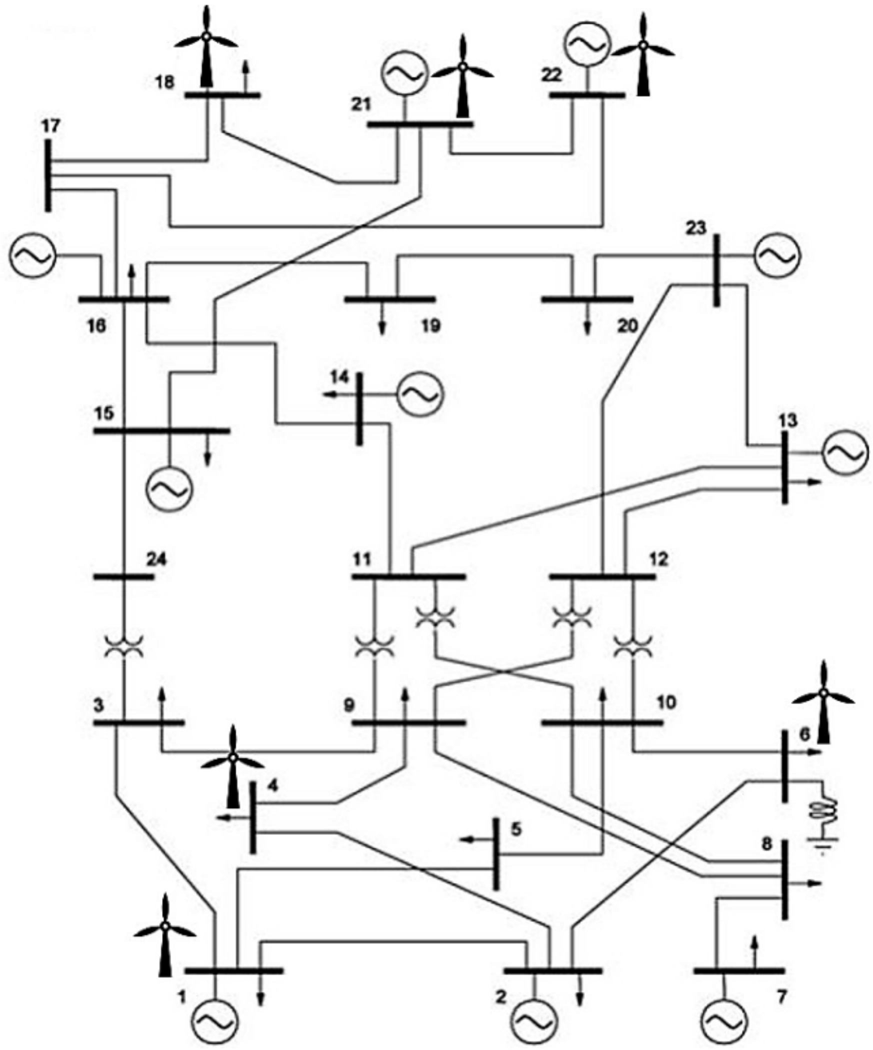

Figure 3.1: Electrical grid

For this model it was assumed that the generation units present their offers in three different linearized segments, between the minimum and maximum production capability, as it can be seen in figure 3.2.

The data regarding the Power of all the twenty-six generators is presented in table 3.1 and each of its start-up cost is presented in table 3.2.

The load profile is divided in three different time periods, Low-Load (01:00-08:00), Off-Peak (09:00-16:00) and Peak (17:00-24:00). For this system, its maximum load is 2850 MW.

For this model the two most pollutant where considered, Nitrogen Oxides (NOx) and Sulfur Dioxide (SO2). The amount of emissions of each of this gases by generator is presented in table 3.3.

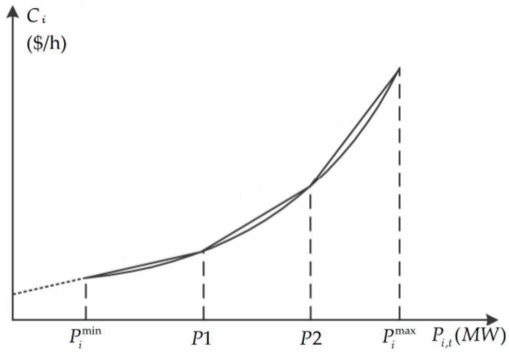

Figure 3.2: Linearized costs by generator segment example

Table 3.1: Power and Cost of each generator

Gen. Units 1 to 5		Gen. Units 6 to 9		Gen. Units 10 to 13		Gen. Units 14 to 16	
Power (MW)	**Cost ($)**	**Power (MW)**	**Cost ($)**	**Power (MW)**	**Cost ($)**	**Power (MW)**	**Cost ($)**
2.4	23.41	15.8	29.58	15.2	11.46	25	18.6
6	23.78	16	30.42	38	11.96	50	20.03
9.6	26.84	19.8	42.82	60.8	13.89	80	21.97
12	30.4	20	43.28	76	15.97	100	22.72
Gen. Units 17 to 20		**Gen. Units 21 to 23**		**Gen. Unit 24**		**Gen. Units 25 and 26**	
Power (MW)	**Cost ($)**	**Power (MW)**	**Cost ($)**	**Power (MW)**	**Cost ($)**	**Power (MW)**	**Cost ($)**
54.25	9.92	68.95	19.2	140	10.08	100	5.31
93	10.25	118.2	20.32	227.5	10.66	200	5.38
124	10.68	157.6	21.22	280	11.09	320	5.53
155	11.26	197	22.13	350	11.72	400	5.66

Table 3.2: Start up cost of each generation unit

Generation Units	1 to 5	6 to 9	10 to 13	14 to 16	17 to 20	21 to 23	24	25 and 26
Start-Up Cost ($)	87.4	15	715.2	575	312	1018.9	2298	0

Table 3.3: Emissions of each generation unit

Generation Units	1 to 5	6 to 9	10 to 13	14 to 16	17 to 20	21 to 23	24	25 and 26
NOx (kg/MWh)	1.14	0.832	3.125	1.85	2.602	3.26	8.33	0
SO2 (kg/MWh)	0.456	0.33	1.25	0.74	1.041	1.304	3.33	0

Regarding the wind farms, in this model they were included in the grid at buses 1, 4, 6, 18, 21 and 22. Each one of these produces up to 150 MW, adding to a total of 900 MW of installed Wind Power. To model the wind power generation, a Weibull distribution for wind speed was considered and by a similar procedure the corresponding wind energy was obtained. In order to be able to represent the inconstancy of this type different scenarios were generated, based on a technique called Roullete Wheel Mechanism. Of the several scenarios generated, only 10 were used in order to reduce computational complexity. The various scenarios used are shown in Figure 3.3.

It was also assumed that each scenario had the same probability of happening, 10%. The wind spillage cost was established at 40$/MWh.

The value of VOLL was defined as 100$/MWh for each load, which means that each 1 MWh loss the system operator has to pay 100$ to the affected consumer.

For this model, the initial price of electricity, is 12,53 \$/MWh. This value was calculated from the average of the market price before the implementation of DR programs. To investigate the efficiency of the DR programs in this electricity grid, the TOU program was applied with different maximum DR potentials.

The electric tariffs of the different cases are presented in table 3.4.

3.3 DR Programs Model

In order to model Demand Response programs it is necessary to define the concept of Elasticity of demand (E) which represents the clients response to changes in electricity prices. Which is the same as saying that if the electricity prices vary for different periods, then the demand reacts. Elasticity is then used with the purpose of estimating the reduction of load by the clients, as well as the load recovery in other periods.

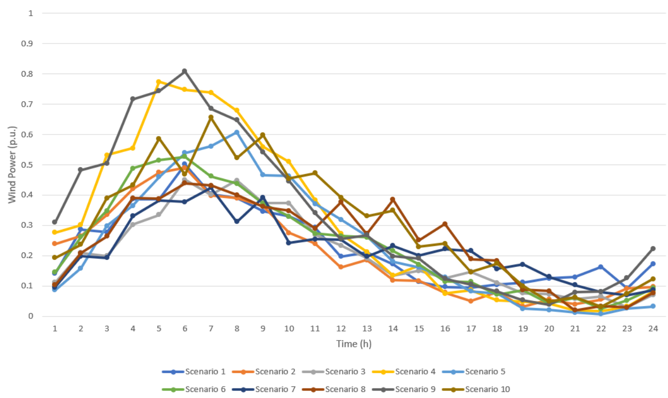

Figure 3.3: Different Wind Power Scenarios

Table 3.4: Electric tariffs of each case

	Low-Load 1h-8h	Off-Peak 9h-16h	Peak 17h-24h
NO DR + NO FR	10.6	10.6	10.6
NO DR + FR	12.53	10.6	10.6
10% DR + NO FR	12.53	14.31	14.31
20% DR + NO FR	12.53	16.09	16.09
10% DR + FR	12.53	14.31	14.31
20% DR + FR	12.53	16.09	16.09

$$E = \frac{\rho_0}{d_0} \cdot \frac{\partial d}{\partial \rho} \tag{3.10}$$

When the energy prices vary loads can have two distinct behaviors, on one hand some loads are not able to move from one period to another, such loads have sensitivity just in a single period (Self-Elasticity) and its value is always negative, as represented in equation 3.11. Some consumption could be transfered from the peak period to the off-peak such behavior is called multi period sensitivity (Cross-Elasticity) which is always positive, as represented in equation 3.12.

$$E_{t,t} = \frac{\triangle d(t)}{\triangle \rho(t)} \leq 0 \tag{3.11}$$

$$E_{t,t'} = \frac{\triangle d(t)}{\triangle \rho(t')} \geq 0 \tag{3.12}$$

3.3.1 Self Elasticity

Assuming the client reduces its demand, from $d_0(t)$ (initial demand) to *d(t)* as a consequence of an incentive or a change of in the electricity price, its obtained:

$$\triangle d(t) = d_0(t) - d(t) \tag{3.13}$$

At the same time IBDRPs impose a cost to the ISO related to the payment of the incentives to the clients for their load reduction. The payment of these incentives can be formulated as follows, where $A(t)$ corresponds to the incentive for the hour t:

$$P(\triangle d(t)) = A(t) \cdot \triangle d(t) \tag{3.14}$$

In this way, the clients Net Benefit (*NB(d(t))* is given by:

$$NB(d(t)) = B(d(t)) - d(t) \cdot \rho(t) + P(\triangle d(t)) \tag{3.15}$$

The first term of the equation, *B(d(t))* is related to the customers revenue, the second term represent the electricity cost and the third term is representative of the incentive. In order to maximize the customers benefit after DR it is required to derive the equation and to be equal to zero:

$$\frac{\partial NB}{\partial d(t)} = \frac{\partial (B(d(t))}{\partial d(t)} - \rho(t) + \frac{\partial P(\triangle d(t))}{\partial d(t)} = 0 \tag{3.16}$$

Which results in:

$$\frac{\partial B(d(t))}{\partial d(t)} = \rho(t) + A(t) \tag{3.17}$$

The Taylor Series expansion for quadratic customers revenue function can be written as following:

$$B(d(t)) = B(d_0(t)) + \frac{\partial B(d_0(t))}{\partial d(t)} \triangle d(t) + \frac{1}{2}\frac{\partial^2 B(d_0(t))}{\partial d^2(t)} (\triangle d(t))^2 \tag{3.18}$$

The customer's net benefit before implementation of DR can be represented as:

$$NB_0(d(t)) = B(d_0(t)) - d_0(t) \cdot \rho(t) \tag{3.19}$$

so,

$$\frac{\partial NB_0(d(t))}{\partial d(t)} = \frac{\partial B(d_0(t))}{\partial d(t)} - \rho_0(t) = 0 \tag{3.20}$$

thus,

$$\frac{\partial B(d_0(t))}{\partial d(t)} = \rho_0(t) \tag{3.21}$$

$$\frac{\partial^2 B}{\partial d^2} = \frac{\partial \rho}{\partial d} = \frac{1}{E}\frac{\rho_0}{d_0} \tag{3.22}$$

Substituting equations 3.21 and 3.22 in equation 3.18 results in:

$$B(d(t)) = B_0(t) + \rho_0(t) \triangle d(t) + \frac{1}{2}\frac{\partial \rho_0(t)}{\partial d(t)} (\triangle d(t))^2 \tag{3.23}$$

Which can be re-written as:

$$B(d(t)) = B_0(t) + \rho_0(t)[d(t) - d_0(t)]\{1 + \frac{d(t) - d_0(t)}{2E(t) \cdot d_0(t)}\} \tag{3.24}$$

Substituting equation 3.24 in equation 3.17:

$$\rho(t) + A(t) = \rho_0(t)\{1 + \frac{d(t) - d_0(t)}{E(t) \cdot d_0(t)}\} \tag{3.25}$$

$$\rho(t) - \rho_0(t) + A(t) = \rho_0(t) \cdot \frac{d(t) - d_0(t)}{E(t) \cdot d_0(t)} \tag{3.26}$$

Therefore, customer's consumption can be represented as the following:

$$d(t) = d_0(t)\{1 + \frac{E(t)[\rho(t) - \rho_0(t) + A(t)]}{\rho_0(t)}\} \tag{3.27}$$

In the case where *A(t)* is equal to zero, this is, where there is no incentive, this is a PBDRP and the consumption is given by:

$$d(t) = d_0(t)\{1 + \frac{E(t)[\rho(t) - \rho_0(t)]}{\rho_0(t)}\} \tag{3.28}$$

3.3.2 Cross Elasticity

In the case where it is possible to transfer loads from the peak period to the off-peak the mathematical formulation can be represented as follows:

$$E(t,t') = \frac{\partial d(t)}{\partial \rho(t')} \cdot \frac{\rho_0(t')}{d_0(t)} \tag{3.29}$$

where,

$$\begin{cases} E(t,t') \leq 0, & \text{if t=t'} \\ E(t,t') \geq 0, & \text{if t=t} \end{cases}$$

According to the concept of cross-elasticity, a slight change in price at the hour *t'* can cause a variation in load at the hour *t*, as following:

$$d(t) = d_0(t) + \sum_{t'=1,t'\neq t}^{24} E(t,t') \cdot \frac{d_0(t)}{\rho_0(t)} \cdot [\rho(t') - \rho_0(t')] \tag{3.30}$$

The customer's response to changes in price are then defined by:

$$d(t) = d_0(t)\{1 + \sum_{t'=1}^{24} E(t,t') \cdot \frac{[\rho(t') - \rho_0(t')]}{\rho_0(t')}\} \tag{3.31}$$

Equation 3.31 shows how much should the consumer's consumption be to achieve maximum benefit in a 24h interval while participating in a PBDRP, where the variations in load only comes from changes in the energy price.

When it comes to IBDRPs, the application of this type of programs comes with a cost to the ISO which implies a slightly different formulation:

$$d(t) = d_0(t) + \sum_{t'=1}^{24} E(t,t') \cdot \frac{d_0(t)}{\rho_0(t')} \cdot [\rho(t) - \rho_0(t') + A(t')] \tag{3.32}$$

On the previous equation, *A(t)* has a positive value in peak hours and zero in the rest.

3.4 Mathematical Formulation

The model proposed aims to optimize both the demand and the production sides, simultaneously. The main goal is to determine the optimal scheduling of production considering different DR programs in order to increase system flexibility and facilitate the integration of wind power.

In order to solve the problem two methods are used: two stage stochastic programming and the Multi Objective (MO) augmented ε constraint. The only stochastic parameter belongs to the Wind Farm generation, which is modeled through different scenarios which allow to take into consideration wind's characteristic variability.

For this problem generation costs, pollutant emissions, losses of load, wind spillage costs, start-up and shut-down costs and reserve costs are also considered. In this sense, the problem is solved through the system operator's point of view.

3.4.1 Objective Functions

The multi objective method, augmented ε constraint, allows the minimization of two different objective functions. For this problem, the two proposed objective functions are, the minimization of operational cost to the ISO (F_{cost}) and the minimization of the emissions of pollutant gases ($F_{emissions}$) from the conventional generation units.

$$Min[F_{cost}, F_{emissions}] \tag{3.33}$$

As referenced before, due to the need of optimizing both the demand and the production side, the two stage stochastic method is the one selected, as it is known for for it's resolution of similar problems. In this way, the objective function given in equation 3.34, is divided in two stages and modeled as showed.

The first terms are the hourly decisions related to the base-case operation cost of generating units. The last term is related to the expected cost changes due to corrective actions as a result of various scenarios. The last part designates the load shedding and wind spillage cost.

$$\begin{aligned} F_{cost} = \sum_t & \left\{ \begin{array}{l} \sum_i [NLC_i \cdot U_{i,t} + C_i^{su} \\ + \sum_m P_{i,t}(m) \cdot C_i(m)] \\ + \sum_i [C_i^{RU} \cdot R_{i,t}^U + C_i^{RD} \cdot R_{i,t}^D \\ + C_i^{FRU} \cdot FR_{i,t}^U + C_i^{FRD} \cdot FR_{i,t}^D] \\ + \sum_p C_{p,t}^{wind} \cdot P_{p,t}^{wind} \end{array} \right\} \\ + \sum_s \sum_t \sum_h w_s \cdot \triangle \cdot & \left\{ \begin{array}{l} \sum_i [C_{i,t}^{RU} \cdot r_{i,s,h,t}^{RU} - C_{i,t}^{RD} \cdot r_{i,s,h,t}^{RU} \\ + C_{i,h}^{FRU} \cdot \triangle FRU_{i,s,h,t} + C_{i,h}^{FRD} \cdot \triangle FRD_{i,s,h,t}] \\ + \sum_j VOLL_{j,h} \cdot LS_{j,s,h,t} \\ + \sum_p C_p^{p\_spill} \cdot P_{p,s,h,t}^{p\_spill} \end{array} \right\} \end{aligned} \tag{3.34}$$

3.4.2 Constraints

3.4.2.1 Thermal Unit Constraints

The power output of conventional generation units and its limit have already been represented in equation 3.4.

Feasible operating ranges of thermal units, including reserve and flexible ramp are depicted in equations 3.35-3.36.

The total reserve capacity plus ramping capacity should not exceed the ramping capability of generating units as shown in equations 3.37-3.38.

Also, the deployed up and down reserve bounds are considered in equations 3.39 and 3.40, respectively. The start-up cost is formulated in equation 3.41.

Also, the minimum up and down time constraints are expressed by equations 3.42-3.43.

The actual real-time production of each thermal unit considering the up/down deployed reserves is defined in equation 3.44.

Actual power production of thermal units considering the flexible ramp is limited by equations 3.45-3.46.

Inequalities defined in equation 3.47 and 3.48 ensure that the actual upward and downward flexible ramp provisions in each sub-hourly time step are positive.

The ramp rate limits of thermal units are modified considering the impact of flexible ramp in equation 3.49-3.50.

$$P_{i,t} + R_{i,t}^{UC} + FRU_{i,t} \leq P_i^{max} \cdot U_{i,t} \tag{3.35}$$

$$P_{i,t} + R_{i,t}^{DC} + FRD_{i,t} \geq P_i^{min} \cdot U_{i,t} \tag{3.36}$$

$$0 \leq R_{i,t}^{UC} + FRU_{i,t} \leq RU_i \cdot U_{i,t} \tag{3.37}$$

$$0 \leq R_{i,t}^{DC} + FRD_{i,t} \leq RD_i \cdot U_{i,t} \tag{3.38}$$

$$0 \leq r_{i,s,t,h}^{up} \leq R_{i,t}^{UC} \tag{3.39}$$

$$0 \leq r_{i,s,t,h}^{dn} \leq R_{i,t}^{DC} \tag{3.40}$$

$$SUC_{i,t} \geq SC_i(U_{i,t} - U_{i,t-1}) \tag{3.41}$$

$$\sum_{t'=t+2}^{t+MUT_i} (1 - U_{i,t'}) + MUT_i(U_{i,t} - U_{i,t-1}) \leq MUT_i \tag{3.42}$$

$$\sum_{t'=t+2}^{t+MDT_i} U_{i,t'} + MDT_i(U_{i,t-1} - U_{i,t-}) \leq MDT_i \tag{3.43}$$

$$P_{i,s,t,h} = P_{i,t} + r_{i,s,t,h}^{up} - r_{i,s,t,h}^{dn} \tag{3.44}$$

$$P_{i,s,t,h} + FRU_{i,t} + \triangle FRU_{i,s,t,h} \leq P_i^{max} U_{i,t} \tag{3.45}$$

$$P_{i,s,t,h} - FRD_{i,t} - \triangle FRD_{i,s,t,h} \geq P_i^{min} U_{i,t} \tag{3.46}$$

$$FRU_{i,t} + \triangle FRU_{i,s,t,h} \geq 0 \tag{3.47}$$

$$FRD_{i,t} + \triangle FRD_{i,s,t,h} \geq 0 \tag{3.48}$$

$$\begin{aligned} &P_{i,s,t,h} - P_{i,s,t,h-1} + (FRU_{i,t} + \triangle FRU_{i,s,t,h}) \\ &+ (FRU_{i,t} + \triangle FRU_{i,s,t,h-1}) \leq \triangle (RU_i U_{i,t} + SUR_i (1 - U_{i,t-1})) \end{aligned} \tag{3.49}$$

$$\begin{aligned} &P_{i,s,t,h-1} - P_{i,s,t,h} + (FRD_{i,t} + \triangle FRU_{i,s,t,h}) \\ &+ (FRD_{i,t} + \triangle FRD_{i,s,t,h-1}) \leq \triangle (RD_i U_{i,t-1} + SDR_i (1 - U_{i,t})) \end{aligned} \tag{3.50}$$

3.4.2.2 Load, Wind Units and Network Constraints

The market equilibria in the base case is shown in equation 3.51.

The DC power flow equation and the transmission flow limits are expressed in equation 3.52 and 3.53, respectively. Note that the widest type of DR programs, the so-called Time of Use (TOU), is modeled here using the price elasticity concept .

So, the modified demand after market-based TOU can be obtained as in equation 3.54 considering a set of rationale constraints represented in equations 3.55-3.58.

Also, wind generation limits are represented in equation 3.59.

$$\sum_i P_{i,t} + \sum_p P_{p,t}^{wind,s} - \sum_j d_{j,t}^{DR} = \sum_l F_{l,t}^0 \tag{3.51}$$

$$F_{l,t}^0 = \frac{(\sigma_{b,t} - \sigma b', h)}{X_l} \tag{3.52}$$

$$-F_l^{max} \leq F_{l,t}^o \leq F_l^{max} \tag{3.53}$$

$$\begin{aligned} d_{j,t}^{DR} = d_{j,t}^0 \Big\{ 1 + \sum_{t' \in LTP} E_{t,t'} [\rho_j^{LTP} - \rho^{ini}] / \rho^{ini} \\ + \sum_{t' \in OTP} E_{t,t'} [\rho_j^{OTP} - \rho^{ini}] / \rho^{ini} + \sum_{t' \in PTP} E_{t,t'} [\rho_j^{PTP} - \rho^{ini}] / \rho^{ini} \Big\} \end{aligned} \tag{3.54}$$

$$\rho_j^{LTP} \leq \rho^{ini} \tag{3.55}$$

$$\rho_j^{LTP} \leq \rho_j^{OTP} \leq \rho_j^{PTP} \tag{3.56}$$

$$\rho_j^{PTP} \geq \rho^{ini} \tag{3.57}$$

$$|d_{j,t}^{DR} - d_{j,t}^{0}| \leq DR^{max} \cdot d_{j,t}^{0} \tag{3.58}$$

$$0 \leq P_{p,t}^{wind,s} \leq P_{p,t}^{wind,max} \tag{3.59}$$

The energy balance is guaranteed in the real-time stage as formulated in equation 3.60. An auxiliary variable is defined in equation 3.61 in order to represent the real-time load variations. Note that the part of load that participates in DR program is assumed to be completely responsible without any uncertainty. Limits on wind power spillage and load shedding are defined in equations 3.62 and 3.63, separately.

$$\begin{aligned} &\sum i(r_{i,s,t,h}^{up} - r_{i,s,t,h}^{dn}) + \sum p(P_{p,s,t,h}^{s} - P_{p,t}^{wind,s} - P_{p,s,t,h}^{p\_spill}) \\ &+ \sum j(d_{j,t}^{DR} - d_{j,s,t,h}^{RT} + LS_{j,s,t,h}) \\ &= \sum_{l} F_{l,s,t,h} - F_{l,t}^{0} \end{aligned} \tag{3.60}$$

$$d_{j,s,t,h}^{RT} = (1 - DR^{max}) \times d_{j,t}^{0} \times d_{s,t,h}^{subhourly} + (d_{j,t}^{DR} - d_{j,t}^{0}) \tag{3.61}$$

$$0 \leq P_{p,s,t,h}^{p\_spill} \leq P_{p,s,t,h}^{s} \tag{3.62}$$

$$0 \leq LS_{j,s,t,h} \leq d_{j,s,t,h}^{RT} \tag{3.63}$$

It is assumed that the ISO has developed a ramp forecast tool to predict the amount of required upward and downward flexible ramp to cope with deviations in the system net load. On this basis, the expected ramp capability requirement to meet the hourly variability plus the variations within each time slot in the real-time stage should be satisfied as in equations 3.64-3.67.

$$\sum_{i} FRU_{i,t} \geq DFRU_{t}^{ex} \tag{3.64}$$

$$\sum_{i} FRD_{i,t} \geq DFRD_{t}^{ex} \tag{3.65}$$

$$\sum_{i} FRU_{i,t} + \triangle FRU_{i,s,t,h} \geq DFRU_{s,t,h}^{RT} \tag{3.66}$$

$$\sum_{i} FRD_{i,t} + \triangle FRD_{i,s,t,h} \geq DFRD_{s,t,h}^{RT} \tag{3.67}$$

In several of the constraints presented other market participants could be included like, Bulk Energy Storages or Photo Electric Parking lots, but these were not considered for this problem.

3.4.3 Augmented ε constraint

The specified method is designed to discover the best points of the Pareto front based on the optimization of one of the objectives, while the other goal is considered as a constraint bound by a range of ε_{kz} values. The problem is solved repeatedly for different values of ε_{kz} to generate the whole set of Pareto.

$$Min(F_1(x) - \delta \sum_{k=2}^{k} \frac{s_k}{r_k}) \tag{3.68}$$

Subject to:

$$F_k(x) + s_k - e_k^z, k = 2, \ldots, K; s_k \in \mathbb{R}^+ \tag{3.69}$$

where:

$$e_k^z = F_k^{max} - (\frac{F_k^{max} - F_k^{min}}{q_k - 1}) \cdot z, z = 0, 1, \ldots, q_k \tag{3.70}$$

On which δ is a scaling factor, s_k is a slack variable, F_{max}^k and F_{min}^k represent the maximum value and minimum of the function based on the Payoff table 3.5.

First, the Payoff table has to be established. This table refers to the values of individual problem optimization for each objective function, considering all constraints.

Table 3.5: Payoff table

	$F_{cost}(\$)$	$F_{emissions}(kg)$
$MinF_{cost}$	F_{cost}^{min}	$F_{emissions}^{max}$
$MinF_{emissions}$	F_{cost}^{max}	$F_{emissions}^{min}$

Chapter 4

Numerical Studies

4.1 Cases in Study

In order to evaluate the efficiency of the model 6 different cases were defined as it can be seen in table 4.1. It is important to note that when a percentage of DR participation is implemented the Demand Response program modeled is TOU.

Table 4.1: Cases in Study

Case	**Program**
1	No DR + No FR
2	No DR + FR
3	10% DR + No FR
4	20% DR + No FR
5	10% DR + FR
6	20% DR +FR

For the proposed problem the main function defined was the cost function, therefore: $F_1 = F_{cost}$ and $F_2 = F_{emissions}$. The payoff tables were obtained from the programmed code and through the individual optimization of each variable in order to obtain the minimum and maximum value for cost and emission for each case, which can be seen in tables 4.2, 4.4, 4.6, 4.8, 4.10 and 4.12, respectively. After obtaining these values they are defined as limits of each Pareto (4.1, 4.4, 4.7, 4.10, 4.13 and 4.16, respectively) curve on which the optimal solution for the problem will be chosen. In order to choose the optimal solution it is assumed that the system operator is responsible for the decision-making. To choose the optimal solution from the Pareto front, obtained through the multi-objective optimization method, it was decided that the emissions value had to be lower than 150000kg. After verifying these conditions the point with the lowest cost is chosen.

In the following sections results regarding each case will be presented and afterwards, a comparative analysis will be done.

4.1.1 NO DR + NO FR

Table 4.2: No DR + No FR Payoff table

	$F_{cost}(\$)$	$F_{emissions}(kg)$
$MinF_{cost}$	410510	143650
$MinF_{emissions}$	785560	103680

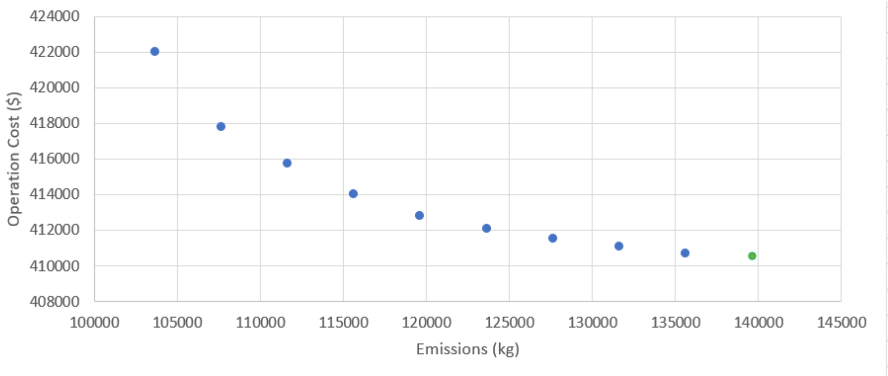

Figure 4.1: No DR+ No FR Pareto Front

As it can be seen in figure 4.1 the optimal solution is the point indicated with a green color and its coordinates correspond to the following:

- $F_{emissions} = 139653kg$;
- $F_{cost} = 410524.60\$$.

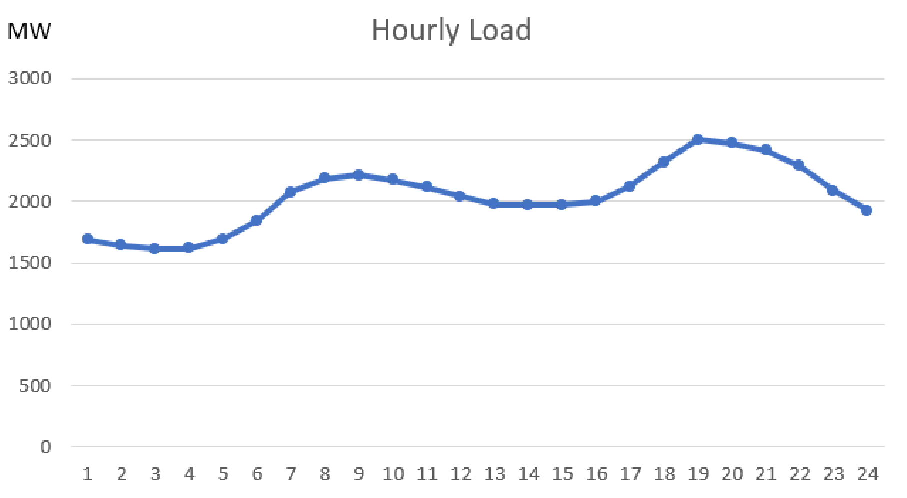

Figure 4.2: No DR+ No FR Hourly Load

Table 4.3: Load Characteristics

Load Factor	$L_{max}(MW)$	L_{avg} **(MW)**
81.52%	2503.10	2040.47

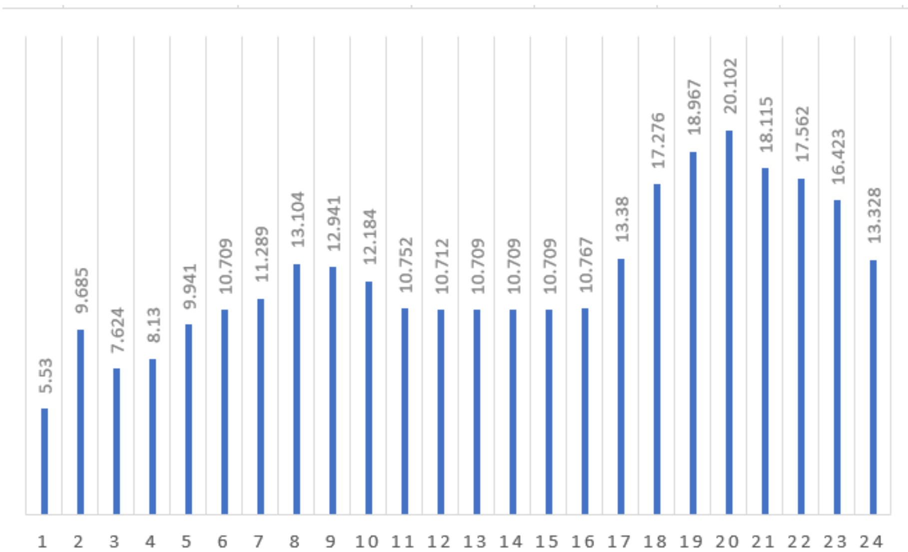

Figure 4.3: No DR+ No FR Marginal Prices ($)

4.1.2 NO DR + FR

Table 4.4: No DR + FR Payoff table

	$F_{cost}(\$)$	$F_{emissions}(kg)$
$MinF_{cost}$	410510	150960
$MinF_{emissions}$	782070	98152.7

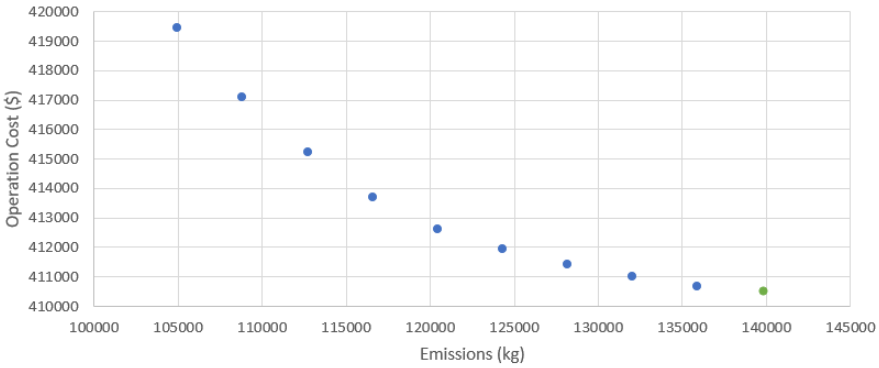

Figure 4.4: No DR+ FR Pareto Front

As it can be seen in figure 4.4 the optimal solution is the point indicated with a green color and its coordinates correspond to the following:

- $F_{emissions} = 139783kg$;
- $F_{cost} = 410523.66\$$.

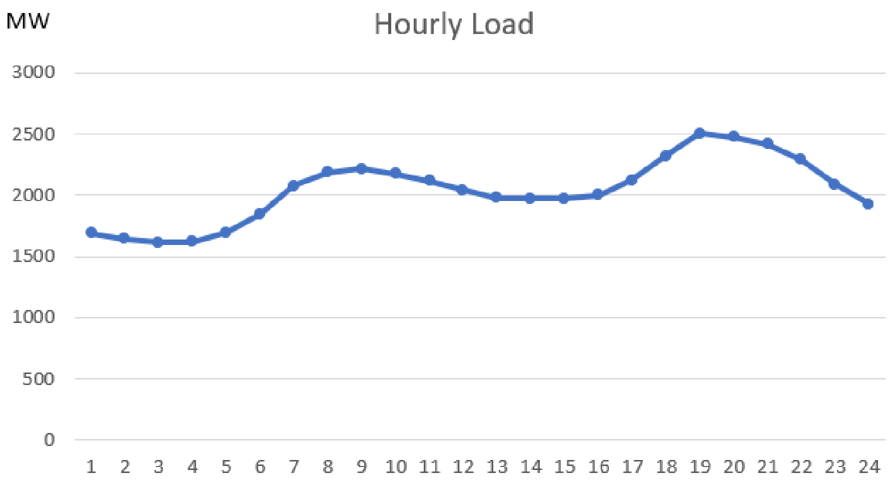

Figure 4.5: No DR+ FR Hourly Load

Table 4.5: Load Characteristics

Load Factor	$L_{max}(MW)$	L_{avg} **(MW)**
81.52%	2503.10	2040.47

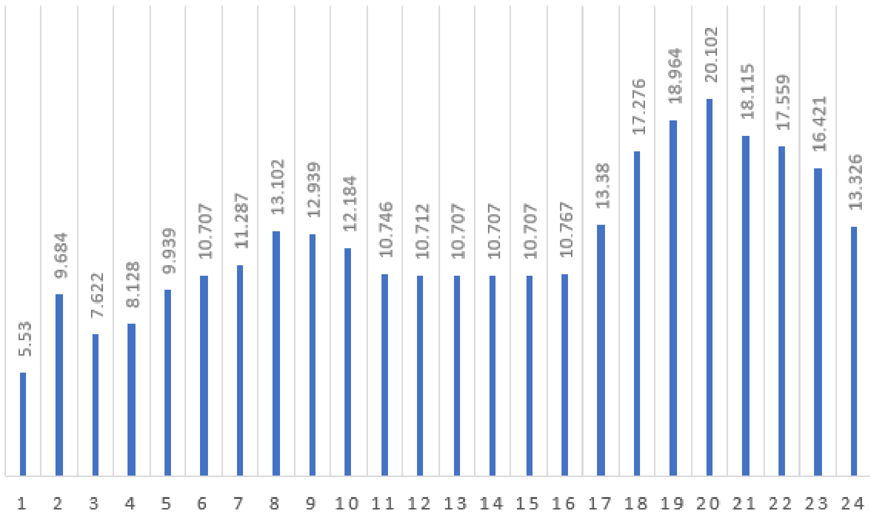

Figure 4.6: No DR + FR Marginal Prices ($)

4.1.3 10% DR + NO FR

Table 4.6: 10% DR + No FR Payoff table

	$F_{cost}(\$)$	$F_{emissions}(kg)$
$MinF_{cost}$	429520	150960
$MinF_{emissions}$	1097900	98152.7

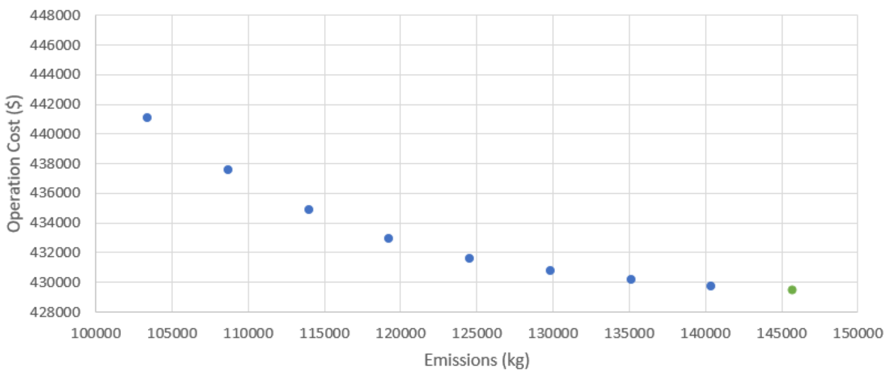

Figure 4.7: 10% DR+ No FR Pareto Front

As it can be seen in figure 4.7 the optimal solution is the point indicated with a green color and its coordinates correspond to the following:

- $F_{emissions} = 145679.27kg$;
- $F_{cost} = 429529.10\$$.

Table 4.7: Load Characteristics

Load Factor	$L_{max}(MW)$	L_{avg} **(MW)**
84.96%	2252.79	1913.99

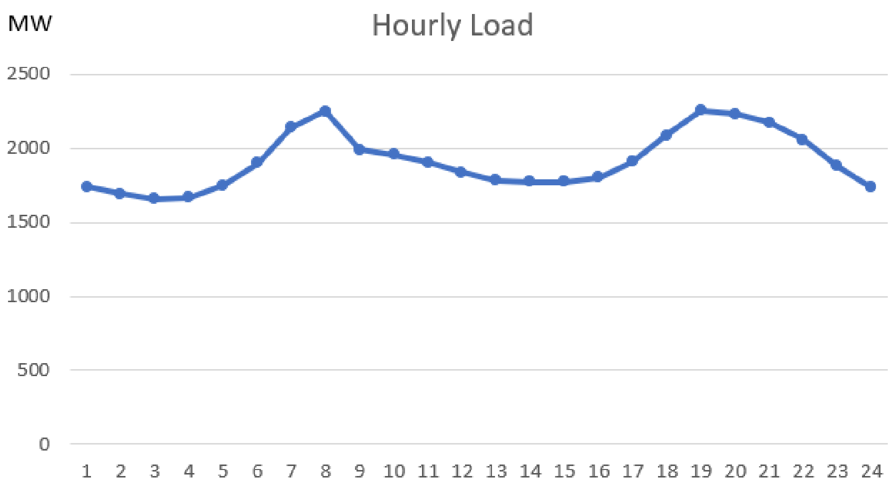

Figure 4.8: 10% DR+ No FR Hourly Load

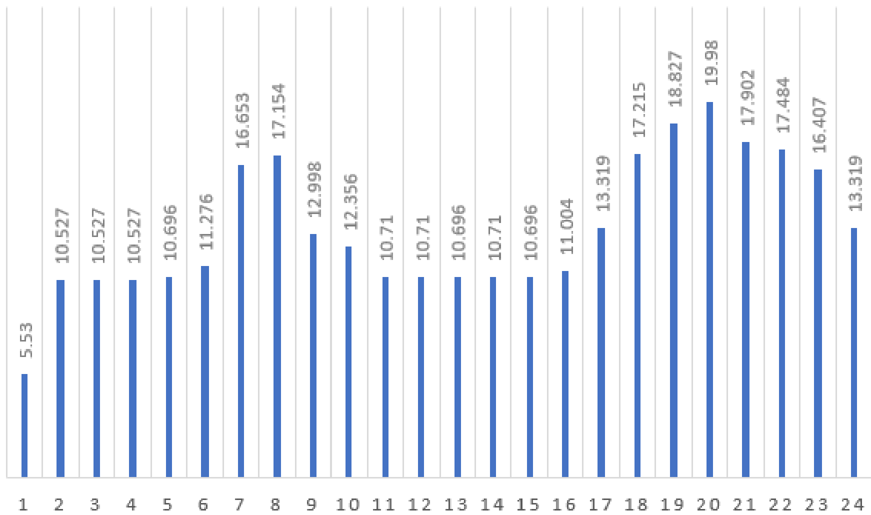

Figure 4.9: 10% DR+ No FR Marginal Prices ($)

4.1.4 20% DR + NO FR

Table 4.8: 20% DR + No FR Payoff table

	$F_{cost}(\$)$	$F_{emissions}(kg)$
$MinF_{cost}$	463620	159280
$MinF_{emissions}$	7022700	90515.9

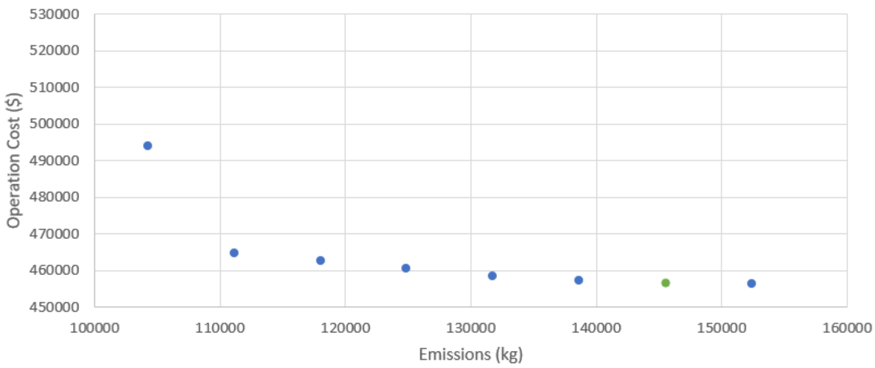

Figure 4.10: 20% DR+ No FR Pareto Front

As it can be seen in figure 4.10 the optimal solution is the point indicated with a green color and its coordinates correspond to the following:

- $F_{emissions} = 145527.08kg$;
- $F_{cost} = 456587.98\$$.

Table 4.9: Load Characteristics

Load Factor	$L_{max}(MW)$	L_{avg} **(MW)**
77.14%	2317.15	1787.52

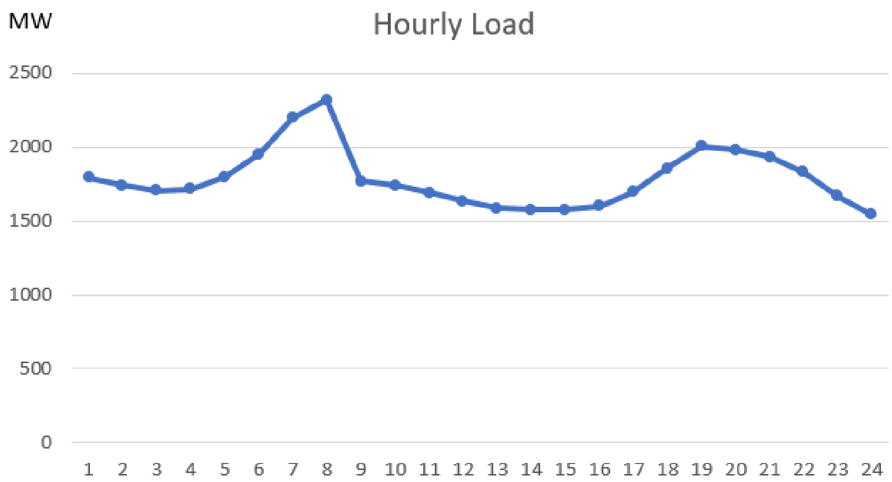

Figure 4.11: 20% DR+ No FR Hourly Load

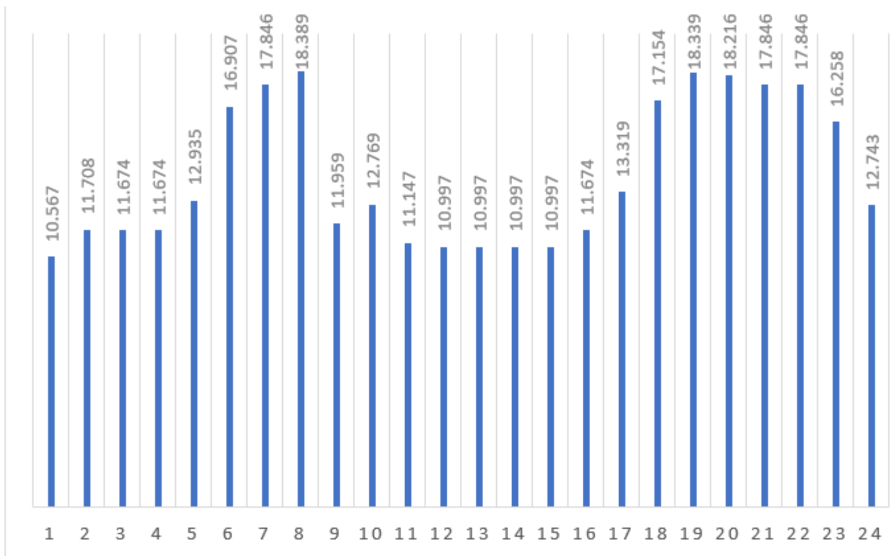

Figure 4.12: 20% DR+ No FR Marginal Prices ($)

4.1.5 10% DR + FR

Table 4.10: 10% DR + FR Payoff table

	$F_{cost}(\$)$	$F_{emissions}(kg)$
$MinF_{cost}$	429520	150960
$MinF_{emissions}$	1113300	96119.1

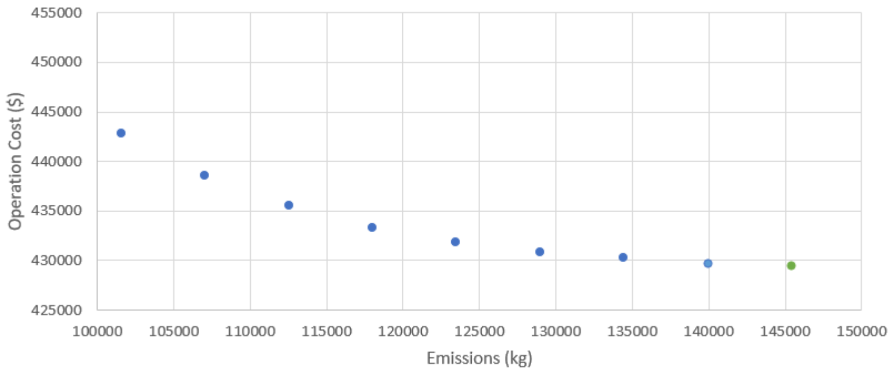

Figure 4.13: 10% DR+ FR Pareto Front

As it can be seen in figure 4.13 the optimal solution is the point indicated with a green color and its coordinates correspond to the following:

- $F_{emissions} = 145385.91kg$;
- $F_{cost} = 429530.43\$$.

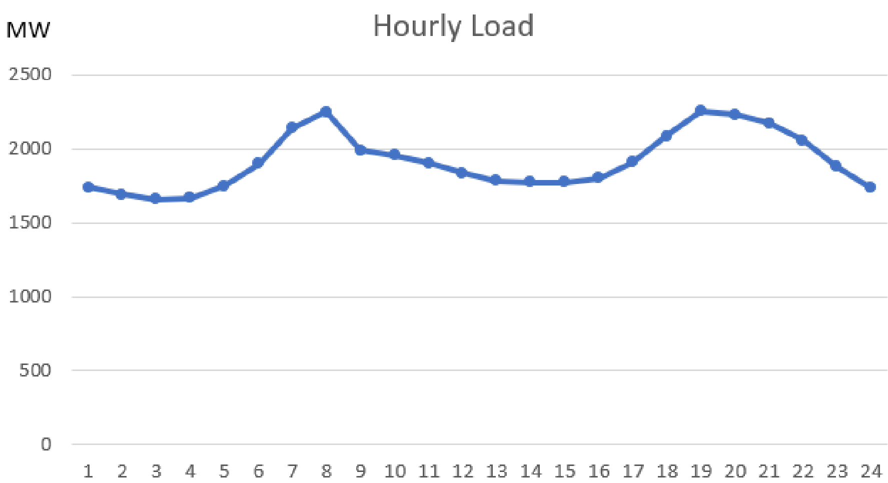

Figure 4.14: 10% DR + FR Hourly Load

Table 4.11: Load Characteristics

Load Factor	$L_{max}(MW)$	L_{avg} **(MW)**
84.96%	2252.79	1914

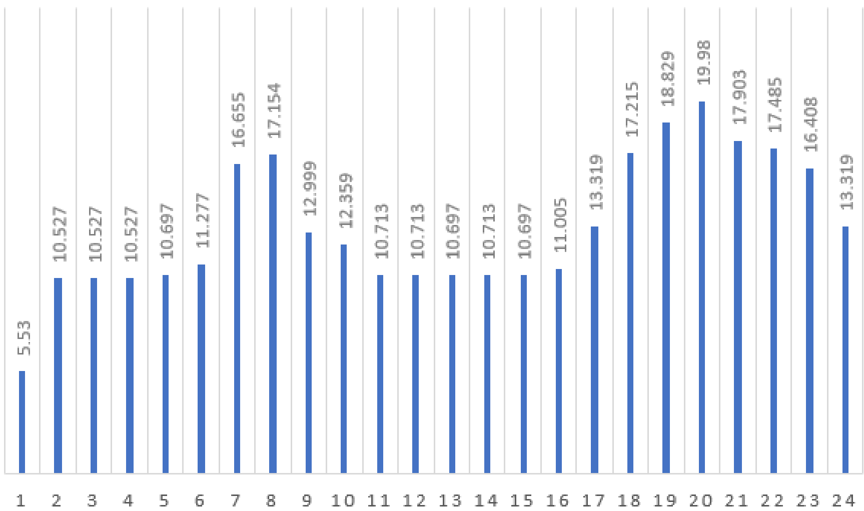

Figure 4.15: 10% DR + FR Marginal Prices ($)

4.1.6 20% DR + FR

Table 4.12: 20% DR + FR Payoff table

	$F_{cost}(\$)$	$F_{emissions}(kg)$
$MinF_{cost}$	456410	156390
$MinF_{emissions}$	1017700	94617.9

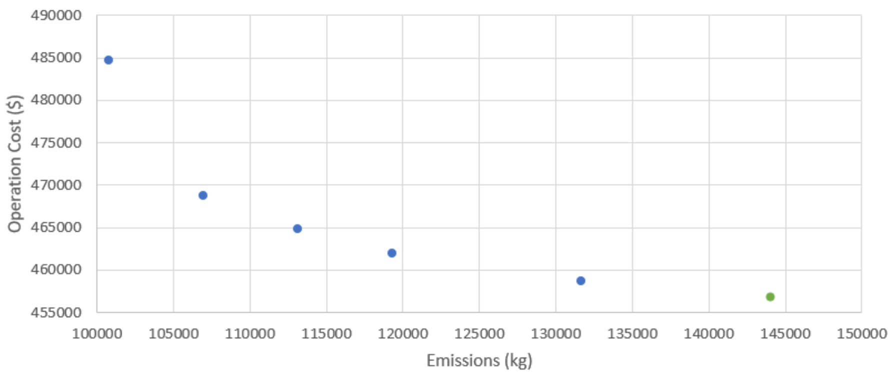

Figure 4.16: 20% DR+ FR Pareto Front

As it can be seen in figure 4.16 the optimal solution is the point indicated with a green color and its coordinates correspond to the following:

- $F_{emissions} = 144035.58kg$;
- $F_{cost} = 456817.65\$$.

Table 4.13: Load Characteristics

Load Factor	$L_{max}(MW)$	L_{avg} **(MW)**
77.14%	2317.15	1787.52

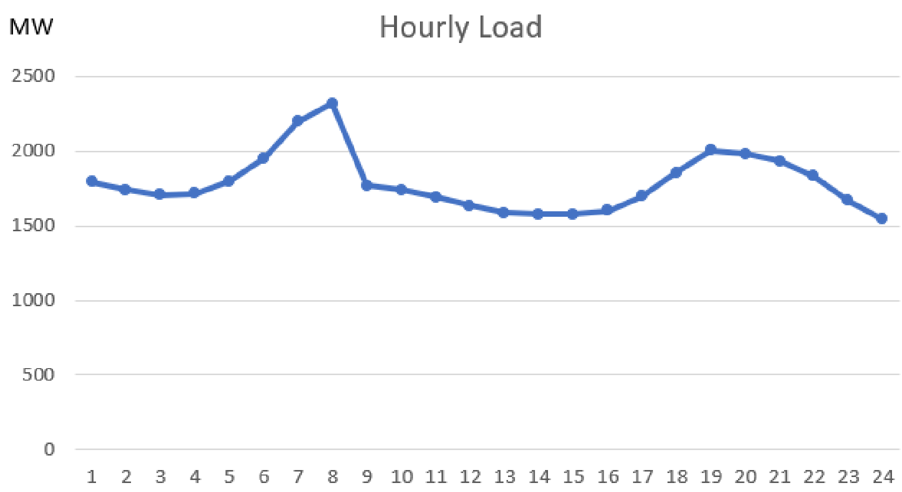

Figure 4.17: 20% DR + FR Hourly Load

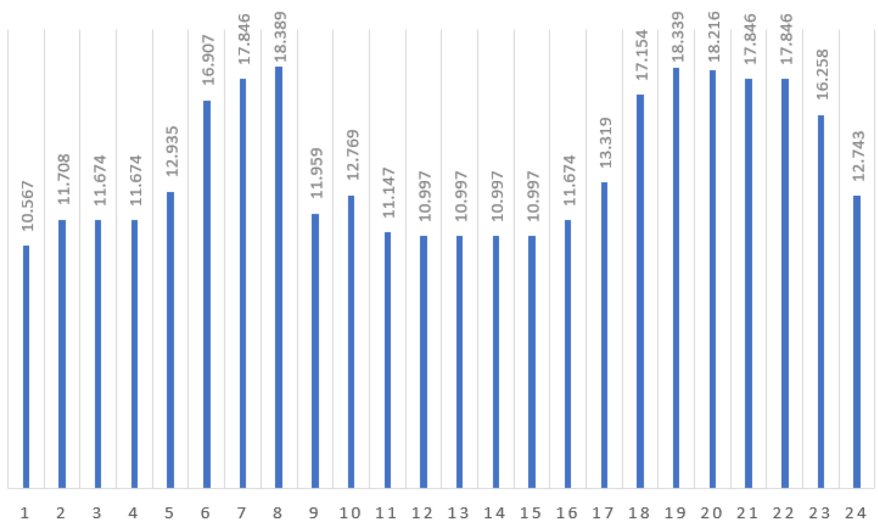

Figure 4.18: 20% DR + FR Marginal Prices ($)

4.1.7 Comparative Analysis

When analyzing the results the first thing worth of note, that can be seen in figure 4.19, is that the implementation of a flexiramp market has no influence in the optimal cost for the system operator, whilst a 10% participation in DR presents an increase of 4% in cost and a 20% participation an increase of 10% from the base case.

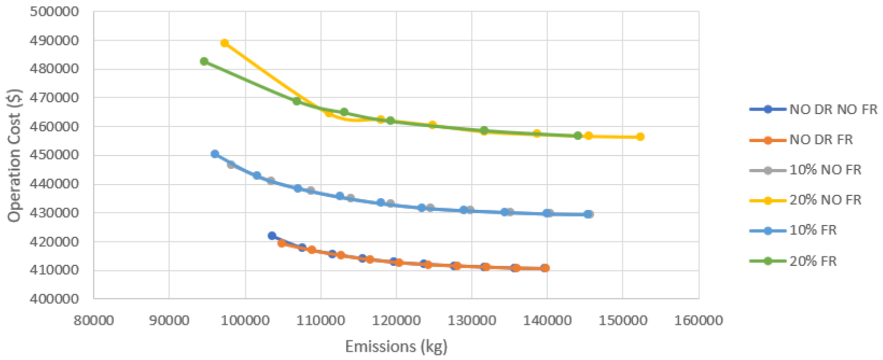

Figure 4.19: Pareto fronts from each case

Table 4.14: Optimal solution for each case

	Emissions (kg)	Cost ($)
NO DR + NO FR	139653.00	410524.60
NO DR + FR	139783.00	410523.66
10% DR + NO FR	145679.27	429529.10
20% DR + NO FR	145527.08	456687.98
10% DR + FR	145385.91	429530.43
20% DR + FR	144035.58	456817.66

The same fact applies to the final load, after implementing Demand Response programs. As the final load is calculated from the original load, the original tariff, the elasticity matrix and the DR tariffs, Flexiramp has no effect on it. Since the load does not change, the electricity price will have insignificant changes. The marginal prices (more accurately: marginal day-ahead prices) with and without FR are not exactly the same (based on the results that prove the correctness of the model) but the changes are not considerable.

As we can see in both 4.20 and 4.21, the values regarding the cases with and without Flexiramp are overlapped or aligned, meaning these share the same values.

Taking a closer look at 4.20, it is noticeable that:

- With the increase in participation in the DR programs, the demand in low-load periods increases implying an increase in prices in those periods.
- Furthermore, and as expected, the implementation of a DR program causes the demand in peak periods to decrease as a consequence of the increase in load prices as it can be seen

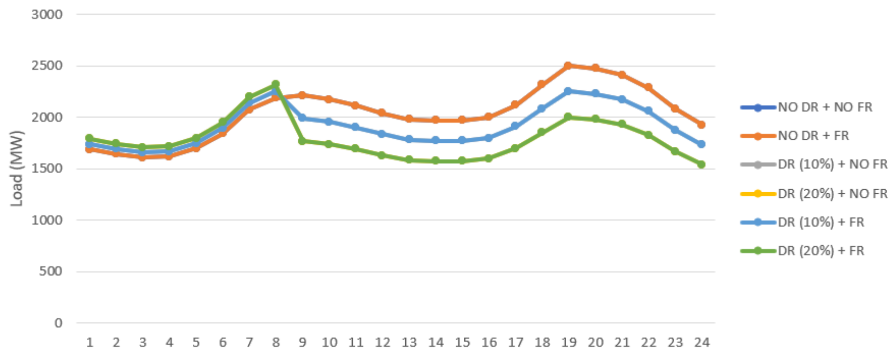

Figure 4.20: Final load after DR from each case

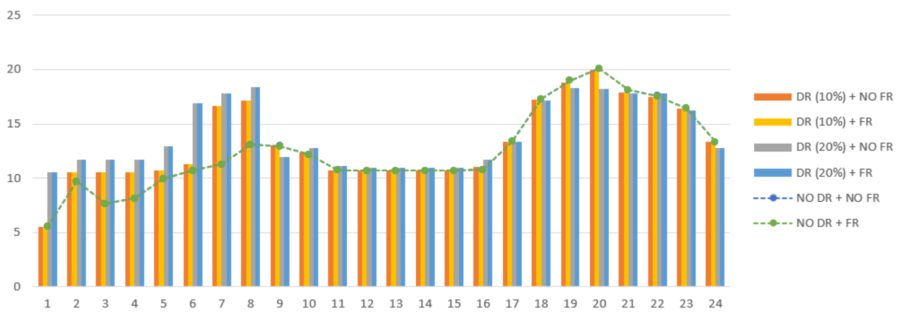

Figure 4.21: Marginal Prices from each case ($)

in 4.22. On the other hand, demand increases in off-peak hours related to the lower prices presented.

- It is vital to notice that the tariffs are outputs of the model. The initial price was set after calculating the average marginal price for the base case and them for each case, the optimal DR tariff is calculated.

- Moreover, as the DR participation increases from 10 to 20% demand in peak hours continues to decrease, leading to the main goal of making the load curve more homogeneous, and avoiding congestion of the transmission lines in peak periods.

- As concluded before, flexiramp has no effect on load, which means that the load characteristics for the cases with and without it will be the same as we can see in the summary table 4.15. Continuing the analysis it is verified that with the application of the DR program the load factor increases when compared to the base. This can be explained with the absence of such a prominent peak period. On the other hand, when the DR participation is increased to 20% the load factor is reduced. The fact can be explained by the continuous reduction of the peak period demand allied with the increase in demand in off-peak hours explained by the reduction in price in that period, which creates a less homogeneous load curve.

- Analyzing the dispatch results it is immediately noticeable that generating units 1 to 9 are not used for any case despite its low emissions. This fact can be explained by the figure 4.23, which shows us that the price per MW of generation units 1 to 5 is 8 to 10 times higher than the more expensive units used (14 to 16) whilst the generation units from 6 to 9 are 2 to 7 times the price.

- As we can see in figure 4.24, FR has no effect on wind spillage has the lines regarding the cases with and without it are overlapped. On the other hand, DR participation level has a direct impact on the wind spillage, as the shifted load can be recovered in the hours that there is high wind generation, in this sense, as the level of participation increases the wind spillage is reduced.

- Regarding RU/RD variables, by increasing the DR participation level, the RD decreases and RU increases. It can also be seen the FR has an impact on decreasing the RD specially when the level of participation is higher. This impact when DR=10% can be also seen, but it is insignificant and is more considerable for DR=20%, in some hours such as 6, 8, 18, 19, and 22 it shows FR can decrease the need for RD. This fact can be confirmed by figure 4.25 and figure 4.26.

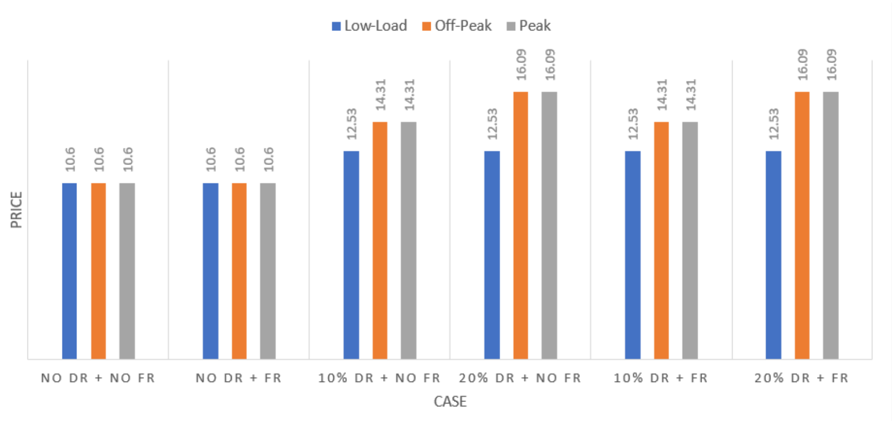

Figure 4.22: Prices per period for each case ($)

Table 4.15: Load characteristics per case

	Load Factor	L_{max}	L_{avg}
NO DR + NO FR	81.52%	2503.10	2040.47
NO DR + FR	81.52%	2503.10	2040.47
10% DR + NO FR	84.96%	2252.79	1914.00
20% DR + NO FR	77.14%	2317.15	1787.52
10% DR + FR	84.96%	2252.79	1914.00
20% DR + FR	77.14%	2317.15	1787.52

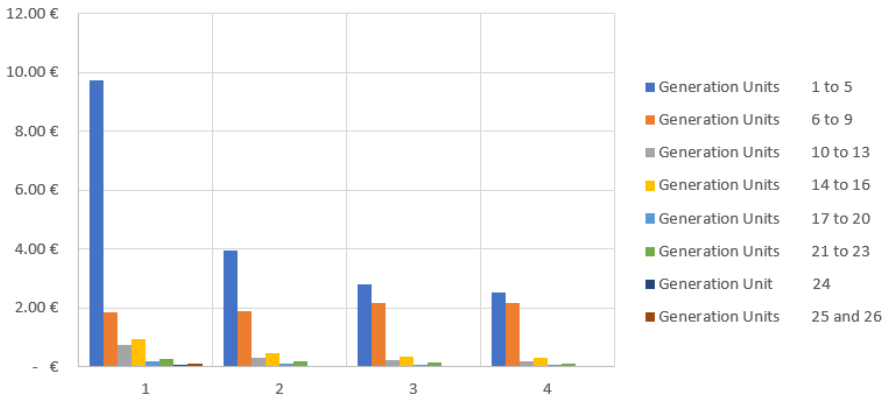

Figure 4.23: Prices per MW of each generation unit

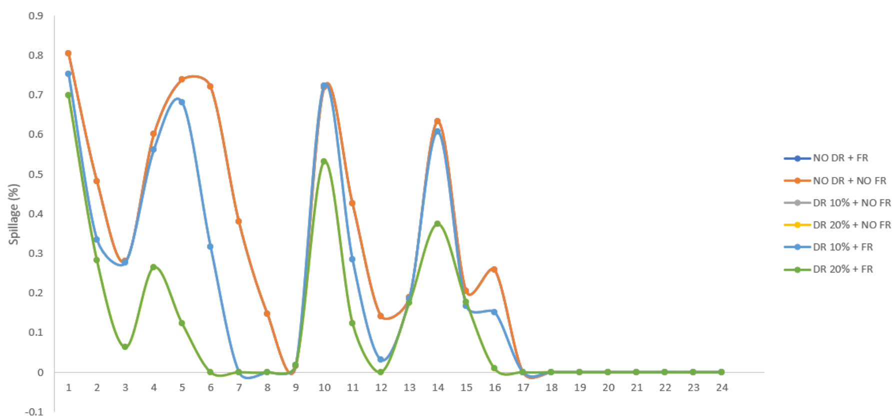

Figure 4.24: Wind Spillage

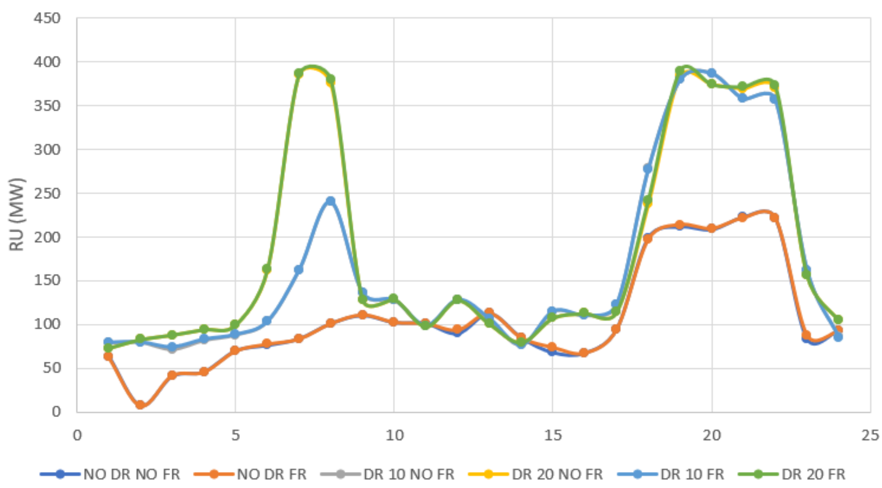

Figure 4.25: Hourly Ramp Up

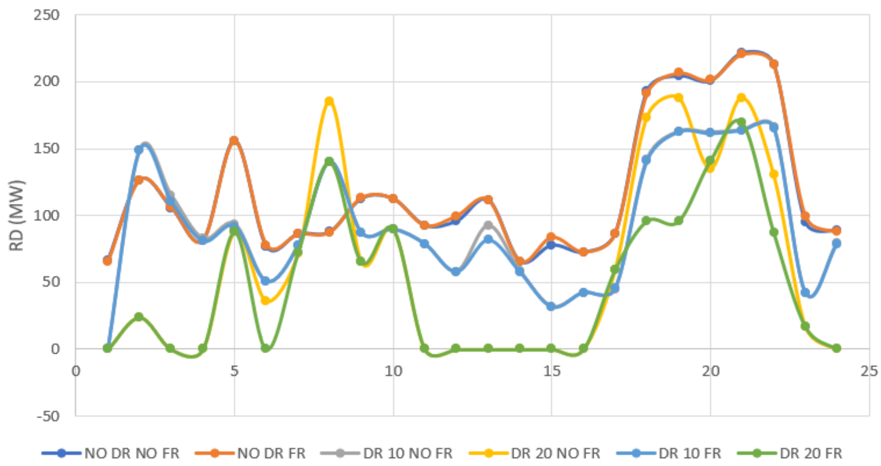

Figure 4.26: Hourly Ramp Down

Making a deep analysis at the Lerner Index, three different cases can be distinguished:

- On one hand, looking at figure 4.27, which represents the Average Lerner index for generation units i10 to i13, it is noticeable that there is an increase on the Lerner value when DR is implemented.
- On the other hand, analyzing figure 4.28, which represents the Average Lerner index for generation units i17 to i20, it is easy to distinguish, not only an increase for the specific case of generator i17 when the DR participation level is of 20%, but also a decrease in the Lerner index for all the other units in all cases.
- Finally, figure 4.29, represents the Average Lerner index for generation unit i24 which presents a decrease in value for when the DR participation is 10% and an increase for a DR participation level of 20%.

A simple study to the index indicates that with the decrease in the Lerner Index value comes an increase in the competitive edge of the market making it more efficient. Taking a deeper look some more conclusions can be drawn.

Figures 4.30, 4.31 and 4.32 represent the hourly Lerner index for a generator representative of each of the cases presented above, and that help us justify them.

For generation unit i10 it is noticeable that the Lerner index assumes higher values during the low-load period and slightly lower values around the peak period, as the DR participation level increases. This makes sense taking into account the changes in hourly load that were verified from figure 4.2 to 4.17.

Analyzing figure 4.31, generation unit i17 Lerner index is slightly lower in the low-load period and higher in off-peak. Finally figure 4.32, shows that generator i24 Lerner index is very stable except for the off-peak period when it is consistently higher, and for peak hours when for the cases where DR participation level gets to 20%.

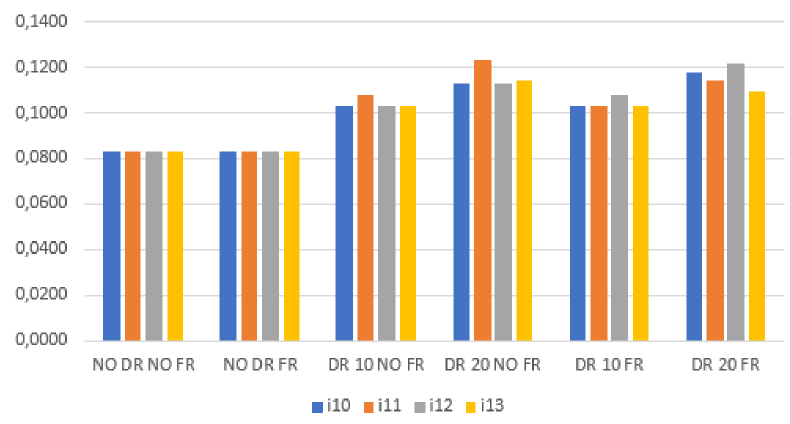

Figure 4.27: Average Lerner Index for generators 10-13 for each case

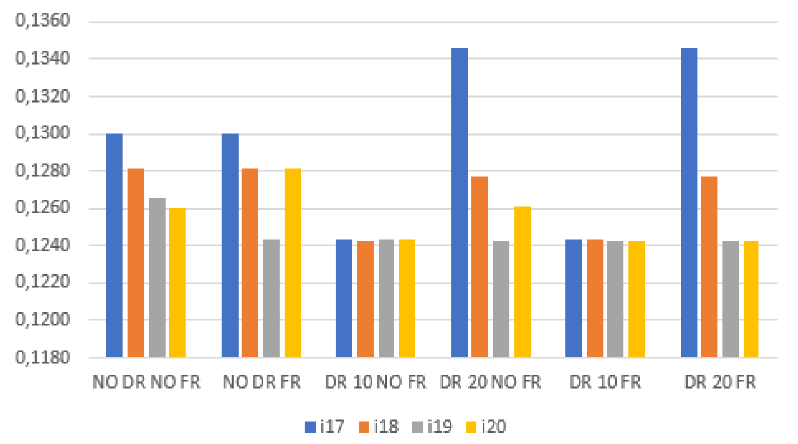

Figure 4.28: Average Lerner Index for generators 17-20 for each case

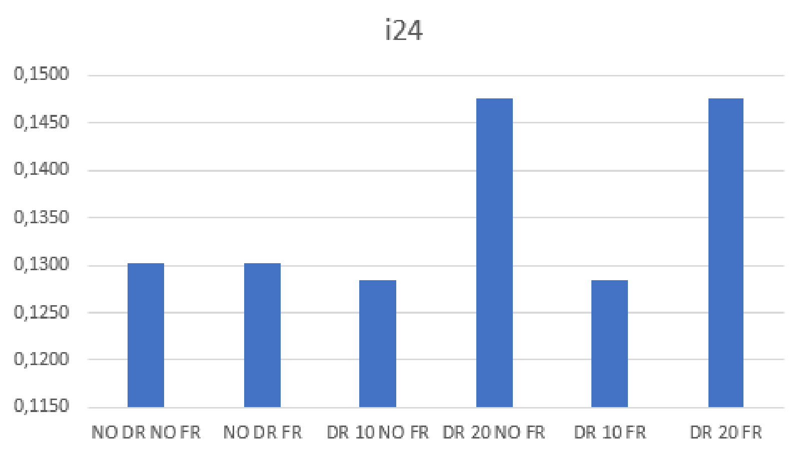

Figure 4.29: Average Lerner Index for generator 24 for each case

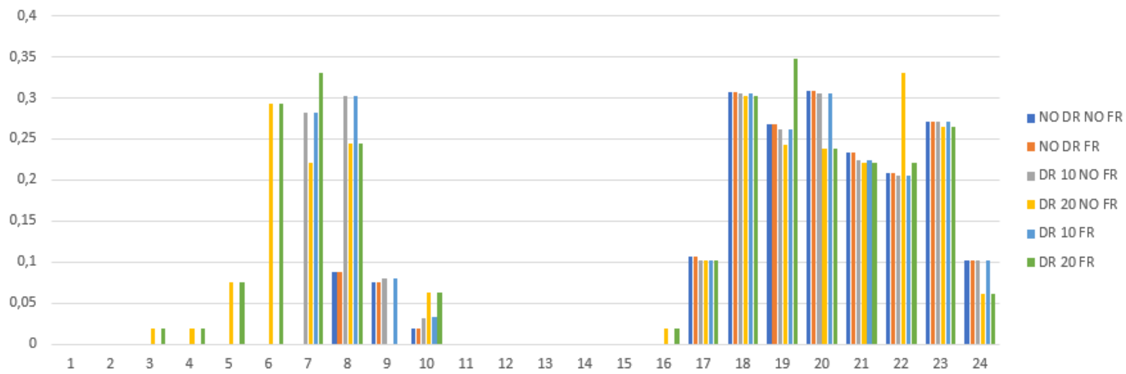

Figure 4.30: Hourly Lerner Index for generator 10 for each case

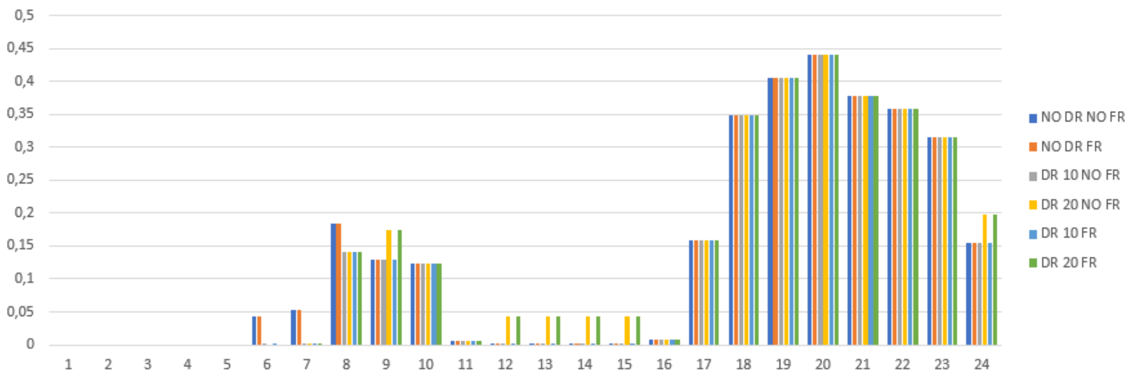

Figure 4.31: Hourly Lerner Index for generator 17 for each case

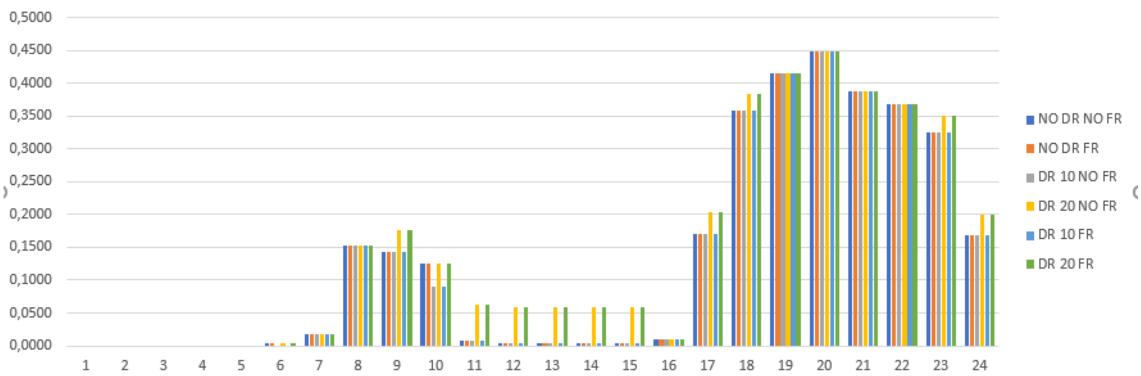

Figure 4.32: Hourly Lerner Index for generator 24 for each case

Chapter 5

Conclusion and Future work

5.1 Conclusion

In response to the need for greater flexibility as a result of the high penetration of RESs, a typical DR program considering the sub-hourly ramp product along with energy and reserve markets was modeled.

This model was solved using a test network with 24 buses including 6 wind farms. In this way, a multi-objective stochastic scheduling method was adopted to dispatch resources and deploy flexible ramp product to cope with the intra-hour variations of wind and load, simultaneously.

Moreover, both the operation cost to the ISO and the reduction of emissions of pollutant gases were to be minimized. However, these objectives conflict since the cheapest generation units are the ones which are more pollutant. For this reason the Augmented ε constraint method was used.

Numerical results presented in Chapter 4, show the analyzes of some different indexes, graphs and tables in order to study the efficiency of DRPs and flexiramp. Six different cases were developed and studied, from the base case without any DR participation and no flexiramp, to a flexiramp market with a DR participation level of 20%.

The first important conclusion drawn was that as the DR participation level increases, a decrease in electrical demand at peak periods and a consequent load recovery at low-load periods in order to balance the load profile is verified. Along with this, it is verified that the implementation of a flexiramp market has no impact on the final load as the final load is calculated from the original load, the original tariff, the elasticity matrix and the DR tariffs. Moreover, since the load does not change, the electricity price will as well have insignificant changes.

Consequently, as the DR participation level increases to 10% making the load curve more homogeneous the load factor increase with it due to the absence of such a prominent peak. This fact is not true for when the DR participation level is 20% as the peak period was just moved to another hour.

Another important conclusion to be drawn is related to wind spillage, which decreases as DR participation level increases, since the shifted load can be recovered in hours of greater wind generation, allowing for a higher penetration of RES.

Finally it could be confirmed that with an increase in DR participation level a flexiramp market can decrease the need for ramping of generation units, which can decrease its wear, and ultimately reduce costs.

It was concluded that, with the implementation of DRPs and a flexiramp market for electrical systems with RES, an increase in the systems flexibility was possible, whilst minimizing the operation costs for the ISO as well as the emissions of pollutant gases.

The proposed model was implemented on a PC equipped with an Intel Core i3-6100 @2.30GHz with 8GB of RAM, and the solution to each case took around 8h to be obtained. In order to retrieve the results from the GAMS a new text editor had to be used since the files were to big to open either in the program itself and the common text editors. Due to this fact a PC equipped with an Intel Core i7-5500 @2.4GHz with 12GB RAM, was used along the text editor, EmEditor to threat the data for further analysis on the previous laptop.

5.2 Future Work

The models proposed in this thesis can be extended to models which integrate Bulk energy storage resources, electric vehicles and it's charging stations.

The impact of other renewable energies such as PV can be studied in the presence of DR and Flexiramp product.

Furthermore, for this thesis, only a voluntary DRP was evaluated, for future works, behavior of customers to mandatory programs, such as DBs, or even to study incentive-based programs can be studied.

5.3 Scientific Contribution

This section presents the publication in peer-reviewed conference proceedings, resulting from the research work carried out in this thesis.

N.G. Santos-Soares, M. Shafie-khah, G.J. Osório, and J.P.S. Catalão "Optimal Dynamic Tariffs for Flexible Ramp Market in the Presence of Wind Energy Generation", in Proceedings of IEEE 18th International Conference on Environment and Electrical Engineering and 2nd Industrial and Commercial Power Systems Europe (EEEIC18/I&CPSE18), 12-15 June, 2018. (Under review).

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