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Investigation on Electricity Market Designs Enabling Demand Response and Wind Generation

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Tese para obtenção do Grau de Doutor em
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(3º ciclo de estudos)

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Engineering

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Thesis submitted in fulfillment of the requirements for the Ph.D. degree in
Electrical and Computer Engineering
(3rd cycle of studies)

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Resumo

A Resposta Dinâmica dos Consumidores (DR) compreende algumas reações tomadas por estes para reduzir ou adiar o consumo de eletricidade, em resposta a uma mudança no preço da eletricidade, ou a um pagamento/incentivo específico. A energia eólica é uma das energias renováveis que tem sido cada vez mais utilizada em todo o mundo. A intermitência e a volatilidade das energias renováveis, em particular da energia eólica, acarretam vários desafios para os Operadores de Sistema (ISOs), abrindo caminho para um interesse crescente nos Programas de Resposta Dinâmica dos Consumidores (DRPs) para lidar com esses desafios. Assim, esta tese aborda os mercados de eletricidade com DR e sistemas de energia renovável (RES) simultaneamente. Vários tipos de DRPs são desenvolvidos nesta tese em ambiente de mercado, incluindo Programas de DR baseados em incentivos (IBDRPs), taxas baseadas no tempo (TBRDRPs) e programas combinados (TBRDRPs) na integração de energia eólica. As incertezas associadas à geração eólica são consideradas através de um modelo de programação estocástica (SP) de dois estágios. Os DRPs são priorizados de acordo com as necessidades económicas, técnicas e ambientais do ISO por meio da técnica para ordem de preferência por similaridade com a solução ideal (TOPSIS). Os impactes dos DRPs na elasticidade do preço e na função de benefício ao cliente são abordados, incluindo as sensibilidades dos parâmetros de DR e dos cenários de potência eólica. Finalmente, um modelo estocástico de dois estágios é aplicado para resolver o problema numa abordagem de programação linear inteira mista (MILP). O modelo proposto é testado num sistema IEEE modificado para demonstrar o efeito da DR na redução do custo de operação.

Palavras Chave

Mercado Elétrico; Operador de Sistema; Programação Estocástica; Programação Linear Inteira Mista; Resposta Dinâmica dos Consumidores; Sistemas de Energia Renovável.

Abstract

Demand Response (DR) comprises some reactions taken by the end-use customers to decrease or shift the electricity consumption in response to a change in the price of electricity or a specified incentive payment over time. Wind energy is one of the renewable energies which has been increasingly used throughout the world. The intermittency and volatility of renewable energies, wind energy in particular, pose several challenges to Independent System Operators (ISOs), paving the way to an increasing interest on Demand Response Programs (DRPs) to cope with those challenges. Hence, this thesis addresses various electricity market designs enabling DR and Renewable Energy Systems (RESs) simultaneously. Various types of DRPs are developed in this thesis in a market environment, including Incentive-Based DR Programs (IBDRPs), Time-Based Rate DR Programs (TBRDRPs) and combinational DR programs on wind power integration. The uncertainties of wind power generation are considered through a two-stage Stochastic Programming (SP) model. DRPs are prioritized according to the ISO's economic, technical, and environmental needs by means of the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method. The impacts of DRPs on price elasticity and customer benefit function are addressed, including the sensitivities of both DR parameters and wind power scenarios. Finally, a two-stage stochastic model is applied to solve the problem in a mixed-integer linear programming (MILP) approach. The proposed model is applied to a modified IEEE test system to demonstrate the effect of DR in the reduction of operation cost.

Keywords

Demand Response; Electricity Market; Independent System Operator; Mixed-Integer Linear Programming; Renewable Energy Systems; Stochastic Programming.

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List of Symbols

The main notations used in Chapters 2, 4 and 5 are listed below. Other symbols are defined where they first appear.

Chapter2

Sets and Indices

b, b'	Index of system buses, $b = 1, \dots, NB$.
i	Index of conventional units, $i = 1, \dots, NG$.
j	Index of loads, $j = 1, \dots, NJ$.
l	Index of transmission lines, $l = 1, \dots, l$.
wf	Index of wind farms, $wf = 1, \dots, NWF$.
t, t'	Index of time periods, $t = 1, \dots, NT$. $t = 1, \dots, NT$
w	Index of scenarios, $w = 1, \dots, NW$.
m	Index of segment for linearized fuel cost, $m = 1, \dots, NM$.

Parameters

d_t^{ini}	Initial electricity demand before DR (MW).
$d_t^{Contract}$	Contracted amounts of load reduction (MW).
$Inc_t \,/\, Pen_t$	Incentive/Penalty values in IBDRPs (\$/MWh).
λ_t^{ini}	Initial electricity price before DR (\$/MWh).
$E_{t,t'}$	Price elasticity of demand.

Chapter 4

Sets and Indices

b, b'	Index of system buses, $b = 1, \dots, NB$.
i	Index of conventional units, $i = 1, \dots, NG$.
j	Index of loads, $j = 1, \dots, NJ$.
l	Index of transmission lines, $l = 1, \dots, l$.
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t, t'	Index of time periods, $t = 1, \dots, NT$. $t = 1, \dots, NT$
w	Index of scenarios, $w = 1, \dots, NW$.
m	Index of segment for linearized fuel cost, $m = 1, \dots, NM$.

Parameters

$C_{i,t,m}^{G\_Eng}$	Offered cost of energy for generating units (\$/MWh).
$C_{i,t}^{G\_UC/DC}$	Offered cost of up/down capacity reserve for generating units (\$/MW).
$C_{i,t}^{G\_UE/DE}$	Offered cost of up/down deployed reserve of generating units (\$/MWh).
$C_{wf}^{WP\_spill}$	Cost of wind spillage (\$/MWh).
SC_i	Start-up cost of unit i (\$).
MUT_i / MDT_i	Minimum up/down time (h).
$P_i^{\min} / P_i^{\max}$	Minimum/Maximum output of units (MW).
RU_i / RD_i	Ramp up/down limits of units (MW/h).
$P_{wf,w,t}^{W}$	Actual wind generation of wind farms (MWh).
$P_{wf,t}^{WP,\max}$	Forecasted wind generation of wind farms (MWh).
$Voll_{j,t}$	Value of lost load j (\$/MWh).
ρ_w	Probability of scenario w.

Variables and Functions

$SUC_{i,t}$	Start-up cost of conventional units (\$).
$U_{i,t}$	Binary on/off status indicator of generation units.
$P_{i,t,m}^{e}$	Generation of segment *m* in linearized fuel cost curve (MWh).
$R_{i,t}^{G\_UC/DC}$	Scheduled up/down reserve capacity of generating units (MW).
$F_{l,t}^{0}$	Power flow through line l at the base case (MW).
$F_{l,w,t}$	Power flow through line l (MW).
$LS_{j,w,t}$	Load shedding of load j (MWh).
$P_{wf,w,t}^{WP\_spill}$	Wind power spillage of wind farms (MWh).
$r_{i,t,w}^{G\_up/dn}$	Deployed up/down spinning reserve of generating units (MWh).
$P_{i,w,t}$	Actual power generation of generation units (MW).

Chapter 5

Sets and Indices

b, b'	Index of system buses, $b = 1, \dots, NB$.
i	Index of conventional units, $i = 1, \dots, NG$.
j	Index of loads, $j = 1, \dots, NJ$.
l	Index of transmission lines, $l = 1, \dots, l$.

wf	Index of wind farms, $wf = 1, \dots, NWF$.
t, t'	Index of time periods, $t = 1, \dots, NT$.
w	Index of scenarios, $w = 1, \dots, NW$.
m	Index of segment for linearized fuel cost, $m = 1, \dots, NM$.

Parameters

$C_{i,t,m}^{G\_Eng}$	Offered cost of energy for generating units ($/MWh).
$C_{i,t}^{G\_UC/DC}$	Offered cost of up/down capacity reserve for generating units ($/MW).
$C_{i,t}^{G\_UE/DE}$	Offered cost of up/down deployed reserve of generating units ($/MWh).
$C_{wf}^{WP\_spill}$	Cost of wind spillage ($/MWh).
SC_i	Start-up cost of unit i ($).
$P_i^{\min} / P_i^{\max}$	Minimum/Maximum output of units (MW).
$P_{wf,w,t}^{W}$	Actual wind generation of wind farms (MWh).
$P_{wf,t}^{WP,\max}$	Forecasted wind generation of wind farms (MWh).
$e_i^{SO_2} / e_i^{NO_x}$	Slope of linearized emission curve of unit i for SO_2 and NO_x pollutants (lbs/MWh).
$IE_i^{SO_2} / IE_i^{NO_x}$	Initial emission of SO_2 and NO_x pollutants (lbs).
ρ_w	Probability of scenario w.

Variables

$SUC_{i,t}$	Start-up cost of conventional units ($).
$U_{i,t}$	Binary on/off status indicator of generation units.
$P_{i,t,m}^{e}$	Generation of segment m in linearized fuel cost curve (MWh).
$P_{wf,w,t}^{WP\_spill}$	Wind power spillage of wind farms (MWh).
$P_{i,w,t}$	Actual power generation of generation units (MW).

Relevant Acronyms

ASDR	Ancillary Service Demand Response.
C/I	Curtailable/ Interruptible Programs.
CAP	Capacity Market Program.
CPP	Critical Peak Program.
DB	Demand Bidding.
DR	Demand Response.
DRPs	Demand Response Programs.
DSO	Distribution System Operator.
EDRP	Emergency Demand Response Program.
EVPI	Expected value of perfect information.
GAMS	General Algebraic Modelling System.
GHG	Greenhouse Gas.
IBDR	Incentive Based Demand Response.
IEA	International Energy Agency.
IREN	International Renewable Energy Agency.
ISO	Independent System Operator.
MADM	Multi-Attribute Decision Making.
MILP	Mixed Integer Linear Programming.
MINLP	Mixed Integer Non Linear Programming.
MODM	Multi-Objective Decision Making.
NO_x	Nitrogen Oxide.
NPV	Net Present Value.
NYISO	New York Independent System Operator.
PBDR	Price Based Demand Response.
PDFs	Probability Distribution Functions.
RESs	Renewable Energy Sources.
RTP	Real Time Programs.
SCUC	Security Constraint Unit Commitment.
S-MILP	Stochastic Mixed Integer Linear Programming.
SO_x	Sulphur Oxide.
SP	Stochastic Programming.
TBRDRPs	Time-Based Rate DR Programs.
TOU	Time of Use.
TSOs	Transmission System Operators.
UCPM	Unit Commitment Program Modeling.
WPPs	Wind Power Producers.

Chapter 1

1. Introduction

1.1 Background and Motivation

Renewable energies, as a solution for environmental issues, have always been a key research area. However, the intermittent nature of such energies may cause economic and technological challenges for Independent System Operators (ISOs), since the acceptable effective solution may exceed the requirement of further investigations.

Although previous studies emphasized employing Renewable Energies and Demand Response (DR) in power systems, each problem was investigated independently, and there have been few studies which have investigated these problems simultaneously. In these recent studies, authors neither analyzed these problems simultaneously nor discussed which scientific and practical aspects of DR and renewable energy injection were employed.

Motivated by this requirement, from the one side this thesis has focused on a comprehensive review of recent research of these cases to provide a reference for future works. From the other side, to increase the sustainability of electrical systems, policy makers have promoted renewable energy technologies. Moreover, concerns about environmental pollution and the ever increasing consumption of fossil fuels, in many of the power systems, have made generators change their electricity generation paradigm to use more renewable energy resources.

Although in recent decades the capacity of renewable energy resources has increased significantly, the evolution of conventional power generators to wind generators has proceeded much more. In general, wind and solar energy are the most applicable forms of renewable energies in the power generation planning and operation. However, wind energy is a rather low-cost energy which has penetrated electrical systems more than other types of renewable energy in recent decades.

Renewable energy is uncertain due to its intermittent nature. Besides, possible ramp variations in power over a short amount of time pose serious challenges. Wind farms can be integrated with Demand Response Programs (DRPs) to reduce side effects of wind fluctuations. The majority of decision makers, power system operators or investors have focused on the advantages and challenges of the proposed DR schemes with specific goals.

Therefore, motivated by this requisite, one part of this thesis is focused on recent studies on DRPs associated with renewable energies and the positive and negative aspects of DR schemes. However, DR systems have not been investigated from this point of view.

The aforementioned renewable energies are boosting substantially to resolve the environmental issues such as the global emission of carbon dioxide and the high consumption of fossil fuels. However, the balancing between supply and demand in power system runs into much more difficulties due to expanding renewable energies. DRPs are a worthy and suitable choice to cope with the intermittent nature of renewable energies [1], [2].

This thesis proposes a DR based operation model of the electricity market considering various types of DRPs, which is one of the most efficient mechanisms to smooth the demand side curve and to compensate the renewable energy fluctuations in the power system [3].

1.2 Research Questions, Objectives and Contributions of the Thesis

Although a number of research works have studied the operation of power systems in the presence of DR and renewable resources, a DR-based operation of energy and reserve markets in the wind integrated systems has not been addressed. In other words, the previous works have defined a supplementary role for the DR in the energy and reserve markets, while this thesis aims at introducing the main role for the DR in the operation of future electricity markets.

Accordingly, a comprehensive model including various types of DRPs is developed for the electricity markets environment, considering the uncertainties of the generation of wind turbines through a two-stage stochastic programming (SP) model. The proposed DR-based operation approach aims at increasing the network security and decreasing the operation cost.

Unlike previous works, the incorporation of market-based DRPs is considered in the proposed model to enhance the substantial role of active customers in the power exchanges of the electricity markets. In order to quantify the effectiveness of the proposed approach, two new indices have also been proposed.

The aforementioned contributions can be summarized as follows:

- Developing a DR-based operation model in the electricity markets with high penetration of renewable energy resources;
- Proposing a comprehensive operation model to incorporate different types of DRPs;
- Introducing two new indices to quantify the impact of DR on the wind integrated power systems.

Although DR programs implementation have been studied in the literature, there is no research so far which analyzed the impacts of a comprehensive set of DR programs including Incentive-Based DR Programs (IBDRPs), Time-Based Rate DR Programs (TBRDRPs) and combinational DR programs on wind power integration. Moreover, most of the previous works investigated the role of DR programs from an economic viewpoint without paying attention to the technical and environmental aspects of DR on the generation mix.

From an economic point of view, the most effective DR program has a higher reduction in system's operation cost, while from a technical perspective it should help to decrease the conventional fleet ramp needed in the presence of stochastic wind generation. Environmentally, an efficient DR program may intercept significant wind power curtailment, thus decreasing emissions.

On this basis, in this thesis, DR programs are prioritized according to the ISO's economic, technical, and environmental needs by means of the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method. It is worth noting that uncertainty surrounding the value of DR is one of the main obstacles to widespread deployment of DR [4]. The price elasticity of demand and customer's participation level in DR programs are two critical factors that have significant impact on DR effectiveness.

In this sense, the sensitivity of each DR program to these vital factors is evaluated as it reveals an interpretation of how the ISO can select a proper DR strategy regarding the DR programs dependency on elasticity and customer acceptance. In short, there are additional contributions to the existing studies from the following aspects:

- To model and analyze a comprehensive set of DR programs including IBDRPs, TBRDRPs and combinational DR programs based on price elasticity and customer benefit function, including the sensitivities of both DR parameters and wind power scenarios;
- To prioritize the performance of various DR programs on economic, technical, and environmental needs of the ISO in the presence of wind power generation;
- To analyze DR programs regarding the customer's elasticity and customer's participation factor as two critical factors to evaluate DR program's performance.

The following research questions will be addressed:

- *How can we manage the operation and propose useful tools to the independent system operator employing demand response programs despite the whole uncertainties surrounding the market, especially pertaining to the wind farms?*
- *What are the impacts of proposed time/price or incentive based demand response programs and their diverse tariffs, on the amount of wind spillage and involuntary load shedding considering the uncertainty of the wind units?*
- *What impacts of modeled time/price or incentive based demand response programs and their various tariffs have been already observed on the operation costs of the system considering the uncertainty of the wind units?*
- *Which are the optimum tariffs among the different DR modeled programs to reach the flexible conditions of the market when there are drastic power shortages of the renewable production units or at the time of a collapse of supply and demand balance?*

- *Which DR programs among the time/price or incentive based demand response programs and their various tariffs have priority in terms of the independent system operator to satisfy the market regulator from the economic, environmental and technical points of view?*
- *What is the relation between the increasing customer participation rate and operation cost?*
- *How much are the DRPs sensitivity to changing the elasticity and the participation rate of the consumers?*

1.3 Methodology

The mathematical models developed in this thesis are based on well-established methods, namely, mixed-integer linear programming (MILP), multi-objective optimization and two-stage stochastic programming. In order to achieve the main research objective, beyond the simulation models, this thesis develops methods and solution strategies to analyze the impact of demand response programs on the system operation under uncertainty, and a dramatically changing power generation scheme over time.

The proposed optimization models and the solutions strategies are implemented in GAMS© and solved in most cases using the CPLEX™ algorithm, mostly by invoking default parameters. The clustering methodology is implemented in the MATLAB© programming environment, and Visual Basic™ with Excel© are used as an interface for this purpose.

1.4 Outline of the Thesis

This thesis project is divided into six chapters.

The current section (Chapter 1) describes the framework of the work involved in the electric power system, which includes the problem statement, objectives, contributions of the thesis, and the techniques and methodologies used in solving the considered problem. The remaining chapters are described below.

Chapter 2 provides a comprehensive overview of the market organization and agents and the decision-making problems they face. Demand Response Programs (DRPs) definition is proposed followed by modelling responsive loads and a detailed classification of recent relevant literature, while the presence of wind resources in the energy market besides wind farms modeling are explained.

Chapter 3 presents the mutual impact of demand response programs and renewable energies. This chapter starts with the definition of different markets, the benefits and costs. Moreover, the integration barriers as well the present/future perspectives are discussed.

Chapter 4 presents the basics of market clearing under uncertainty considering wind energy. It provides a general view of some of the most important issues surrounding the large-scale usage of wind energy in current power systems. This chapter introduces the market clearing model to manage wind power uncertainty emphasizing the differences with respect to the treatment of equipment failures. Moreover, two performance metrics providing condensed information on the benefits and costs of wind integration are presented.

Chapter 5 prioritizes the effectiveness of a comprehensive set of demand response programs on wind power integration. In order to simulate the two-stage operation of day-ahead and real-time electricity markets in the presence of wind power uncertainty, the result of a two-stage stochastic market clearing model is presented in this chapter. The multi criteria decision making procedure is explained and the numerical studies are conducted.

Chapter 6, which is the final chapter, presents the work accomplished and the publications so far. It presents the main conclusions of this work. Guidelines for future works in these fields of research are provided. Moreover, this chapter reports the scientific contributions that resulted from this research work and that have been published in journals, book chapters or conference proceedings of high standard (IEEE).

1.5 Notation

The present thesis uses the notation commonly used in the scientific literature, harmonizing the common aspects in all sections, wherever possible. However, whenever necessary, in each section, a suitable notation may be used.

The mathematical formulas will be identified with reference to the subsection in which they appear and not in a sequential manner throughout the thesis, restarting them whenever a new section or subsection is created. Moreover, figures and tables will be identified with reference to the section in which they are inserted and not in a sequential manner throughout the thesis.

Mathematical formulas are identified by parentheses (x.x) and called “Equation x.x” and references are identified by square brackets [xx]. The acronyms used in this thesis are structured under synthesis of names and technical information coming from the English language, accepted in the technical and scientific community.

Chapter 2

2. Literature Review

2.1 Introduction

This chapter provides an overview of the organization and agents of a typical fully-fledged electricity market, and outlines the decision-making problems faced by these agents. The time framework and the uncertainties are also discussed. For further information, relevant references analyzing electricity markets, their organization and agents, include [5], [6].

This chapter is organized as follows. Section 2.2 provides a general description of the most common electricity market organization and the roles of the market agents. Section 2.3 presents Demand Response Programs (DRPs) definition and classifications. Section 2.4 explains about the presence of wind resources in the energy market and modeling of the wind farms.

2.2 Organization and Agents

Over the last decades, the electric energy industry has evolved from a centralized operational paradigm to a competitive one in many countries all over the world. This new competitive framework is intended to promote an increase in the operational efficiency of power systems while guaranteeing an acceptable quality of the electricity supply and achieving minimum cost for electricity end users.

In addition, it is aimed to provide better incentives for capital formation, better incentives for consumers to not consume when costs exceed their benefits, and better incentives for research and development. This restructuring process has enabled the liberalization of the electricity sector and the emergence of electricity markets worldwide.

2.2.1 Market Organization

Two different trading arenas are usually available to facilitate energy commerce between producers and consumers and are called pools and futures markets. The pool is a marketplace where the energy is traded on a short-term basis. It typically includes:

1. A day-ahead market.
2. Several adjustment markets (not in US markets).
3. Balancing markets (also called real-time markets).

These markets are described in Subsection 2.2.3. The day-ahead and adjustment markets cover generally the bulk of energy transactions within a day. The adjustment markets are similar to the day-ahead market but are cleared closer to power delivery and may cover a shorter trading horizon.

Complementarily, the balancing market allows the short term covering of dispatched power that does not materialize due to equipment failures or the intermittent nature of some sources (e.g., wind or solar-thermal power plants). It also allows covering load deviations and sometimes deals with transmission constraints.

On the other hand, the futures market allows electricity trading on a medium- or long-term horizon by means of purchases and sales of standard products, called derivatives or derivative products. This market is described in Subsection 2.2.4. There also exists the possibility of signing bilateral contracts between suppliers and consumers. A bilateral contract is a free arrangement between a supplier and a consumer defined outside an organized marketplace.

Figure 2.1 illustrates how bilateral contracts take place. Producers sign bilateral contracts with consumers or retailers. Consumers buy energy for their own consumption, while retailers buy energy to supply their clients' demands. Consumers deal directly with producers while retailers' clients deal with producers through their retailers. The arrows in this figure indicate the flow of energy.

Other markets are also needed to ensure the secure system operation and energy delivery, namely, reserve and regulation markets. The reserve market, cleared once a day, provides standby power (spinning and non-spinning) to cover the failure of facilities in operation (production units or transmission lines), large fluctuations of demand, and the intermittent energy generation from non-dispatch-able sources, such as wind farms and solar-thermal production facilities. In most US market (e.g., MISO, www.midwestiso.org), energy and reserve are co-optimized by using a single clearing procedure involving both energy and reserve.

The regulation (automatic generation control, AGC) market provides up and down real-time load-following capability to enforce continuously the balance between production and consumption (and to keep fixed the system frequency), a hard technical requirement of electric energy systems. The regulation market is typically cleared once a day on an hourly basis and assigns to production units the power bands to be used in real-time operation for load following.

Figure 2.2 illustrates the organization of a fully-fledged electricity marketplace, including the futures market and the pool, which are energy markets, and the reserve and regulation markets, which are markets to acquire capacity commitments. Generally, market operators (MO) clear the futures market and the pool, while the independent system operator (ISO) clears the reserve and the regulation markets. In most US markets, futures markets are managed and cleared by for-profit entities.

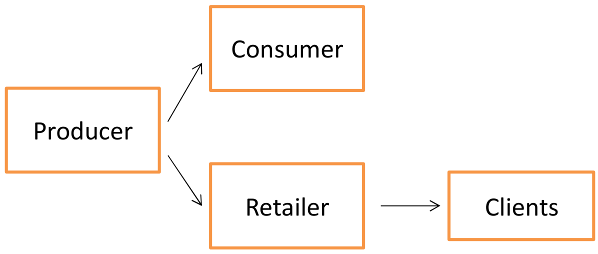
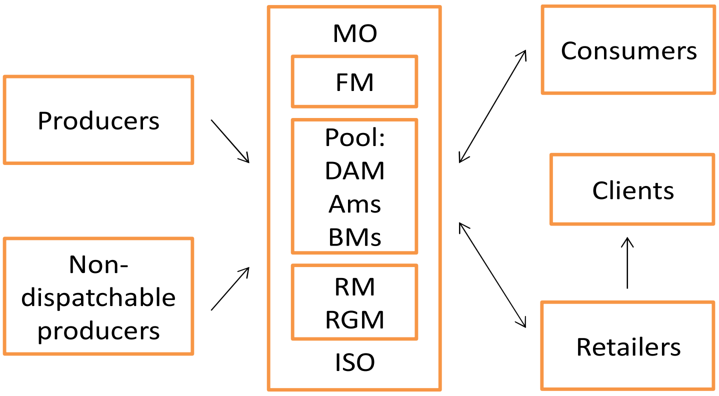


Figure 2.1- Bilateral contracting of electricity.



FM: futures market, DAM: day-ahead market, AMs: adjustment markets, BMs: balancing markets, RM: reserve market, RGM: regulation market.

Figure 2.2-Electricity Marketplace.

Producers sell energy, reserve and regulation, while consumers and retailers buy energy and may sell reserve as well. Arrows indicate the flows of energy, reserve power, and balancing energy.

Services required for the appropriate functioning of the electric energy system and not provided generally via markets include reactive power management and voltage control, system restoration after a blackout, etc. These services are not studied in this context.

2.2.2 Agents

Agents participating in electricity markets are briefly described below. These market agents include consumers, retailers, producers, and non-dispatch-able producers:

<u>1. Consumers</u>. They are the end users of the electricity. They may purchase Energy in the pool or in the futures market, or may sign bilateral contracts with producers or be supplied by retailers. A consumer aims to either minimize its procurement cost or to maximize the utility it obtains from electricity usage.

Additionally, a consumer may participate in the reserve market if it is willing to change its consumption within pre-specified limits at the command of the independent system operator. A consumer may need to participate in the balancing market if its consumption pattern deviates from that settled in the pool.

2. Retailers. They provide electricity to those consumers that do not participate directly in the electricity markets. Retailers do not generally own production units and they purchase the electricity to be supplied to their clients through bilateral contracts, in the futures market, and in the pool.

The objective of a retailer is to maximize the profit it obtains from selling to its customers. Its profit margin is generally narrow as it should buy as cheap as possible to provide its clients with the lowest possible prices; otherwise these clients may change retailer. Marketers play the same role as retailers but may also intermediate between producers and retailers.

3. Producers. They are the entities owning the production units that are in charge of the electricity generation. A producer may sell electric energy either to the electricity markets (pool and futures market) or directly to the consumers and the retailers through bilateral contracts. The objective of a producer is to attain maximum profit from the sale of electricity and eventually reserve and regulation.

A producer may participate in both the reserve and the regulation markets, providing, respectively, reserve power and load following capacity within pre-specified power bounds. If beneficial, a producer may also participate in the balancing market to cover the excess/deficit of generation/demand.

4. Non-dispatch-able producers. They are producers with non-dispatch-able sources, such as wind or solar-thermal power plants. All market agents must cope with the intermittency and time-dependent nature of non-dispatch-able sources. A non-dispatch-able producer strives to maximize the profit from selling in the pool the energy it produces in an intermittent manner. A non-dispatch-able producer needs to participate in the balancing market to cover its deviations from the production pattern settled in the pool.

Institutional market agents include the Market Operator (MO), the ISO, and the Regulator:

- Market Operator (MO). It is generally a nonprofit entity responsible for the economic management of the marketplace as a whole. In addition, the market operator administers the market rules and determines the prices and quantities of energy traded in the market. In some cases, the MO is a for-profit regulated entity;
- Independent System Operator (ISO). It is a nonprofit entity in charge of the technical management of the electric energy system pertaining to the electricity market. The independent system operator should provide equal access to the grid to all consumers, retailers and producers, and strive to facilitate the commerce among buying and selling agents;
- The independent system operator manages generally the reserve and the regulation markets, and assists the market operator to clear the balancing market;
- Market Regulator. It is a government-independent entity whose function is to oversee the market and to ensure its competitive and adequate functioning. Additionally, the regulator promotes and enforces orders and regulations.

In some markets, such as the PJM Interconnection and ISO New England, the functions performed by the independent system operator and the market operator are carried out by a single entity.

In this case, the independent system operator is in charge of both the technical control of the system and the economic management of the market. However, futures markets are managed by independent for-profit entities.

2.2.3 Pool

The pool comprises a day-ahead market and several shorter-term markets known as adjustment markets. It also includes the balancing market that ensures the real-time balance between supply and demand. The pool organization and its functioning are illustrated in Figure 2.3.

Producers submit production offers while consumers and retailers submit consumption bids to the day-ahead, adjustment, and balancing markets, and in turn, the market operator clears these markets and determines prices and traded quantities. Thin arrows indicate the flows of offers and bids, while the thick arrow indicates market outcomes.

The energy traded in the pool is mostly negotiated in the day-ahead market, while adjustment markets are used to make adjustments to the energy cleared in the day-ahead market. The balancing market allows last minute energy adjustments. Since trading mechanisms closer in time to the power delivery allows a higher accuracy on actual power production forecasts by intermittent sources, non-dispatch-able producers tend to rely more on adjustment markets than conventional producers.

In the day-ahead and adjustment markets, producers submit energy blocks and their corresponding minimum selling prices for every hour of the market horizon and every production unit. At the same time, retailers and consumers submit energy blocks and their corresponding maximum buying prices for every hour of the market horizon. The market operator collects purchase bids and sale offers, and clears the market (both day-ahead and adjustment) using a market-clearing procedure.

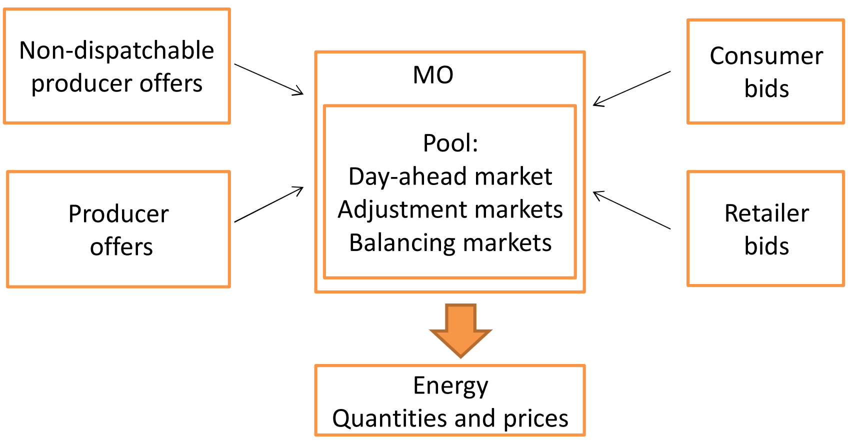


Figure 2.3- Pool organization and functioning.

A market-clearing procedure results in market-clearing prices, as well as production and consumption schedules. If the transmission grid is not considered in the market-clearing procedure, the resulting market-clearing price is identical for all market agents.

On the other hand, if the transmission network is taken into account for clearing the market, instead of a single market-clearing price, a locational marginal price (LMP) is associated with each node of the power system. LMPs differ across nodes due to line losses and line congestion. If a transmission line is congested, more expensive generation is needed to be dispatched on the downstream side of the congested line. This increase in expensive generation yields an increase in the market-clearing prices in those nodes placed on the downstream side of the congested line.

The balancing (or real-time) market, cleared on an hourly basis (or several times within each hour) through an auction, provides energy to cover both generation excess and deficit, and constitutes the last market prior to power delivery to balance production and consumption. Producers/consumers submit balancing offers that are accepted by the market operator on an increasing price basis until balance is guaranteed in the case of deficit of generation. Alternatively, for the case of excess of generation, offers to reduce production are accepted on a decreasing price basis until balance is ensured.

Figure 2.4 illustrates the organization and functioning of the balancing market. Producers participate providing balancing (up and down) energy, while non-dispatch-able producers and consumers use this market to self-balance their energy productions and consumptions, respectively, to those values agreed in previous pool markets. Retailers, which behave as consumers, are not represented in this figure for the sake of simplicity. The balancing market ensures a balanced system operation. Moreover, thin arrows indicate the flows of balancing energy, while the thick arrow indicates market outcomes.

Producers and consumers participate in this market by changing their respective production and consumption dispatches if profitable. Consumers may need to participate in the balancing market if they cannot control their consumption patterns and these patterns deviate from previous pool agreements.

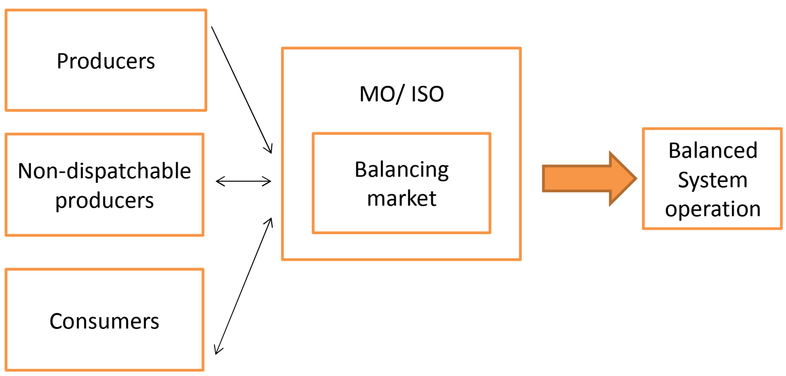


Figure 2.4- Organization and functioning of the balancing market.

Non-dispatch-able producers do need to participate in the balancing market due to the intermittent and uncertain nature of their production sources, which makes generally impossible to comply with a previously agreed production pattern. Finally, it is relevant to note that in some pool-based markets, the time span is divided into periods shorter than one hour. For example, in the New Zealand electricity market, offers are submitted on a 30-minute basis. In most electricity markets, the main characteristics of pool prices are:

- Non-stationary mean and variance, multiple seasonality, calendar effect, high volatility, and high percentage of outliers [7], [8]. Due to these characteristics, pool prices are hard to forecast. However, information about future pool prices is crucial for market agents to bid in the pool and to trade in the futures market;
- Electricity pools in Europe include:
  - The Electricity Pool in the UK (www.apxgroup.com);
  - Nordpool in Scandinavia (www.nordpool.no), and;
  - OMEL in the Iberian Peninsula (www.omel.es).
- Pools in the US include:
  - ISO New England (www.iso-ne.com) and;
  - PJM Interconnection (www.pjm.com).

2.2.4 Futures Market

A futures market is an auction market in which participants buy and sell physical or financial products for delivery on a specified future date. These products are called derivatives or derivative products [9]. The most salient feature of futures markets is that they allow trading physical or financial products in the future at today prices. Thus, futures markets are useful if the price of electricity is highly uncertain in the pool, which is the case in pool-based electricity markets.

Pool prices (day-ahead, adjustment, and balancing) exhibit a set of characteristics such as high volatility, high percentage of outliers, etc., and such characteristics make pool prices highly uncertain. Uncertainty in the pool is undesirable since it is the main cause of volatility of profits or costs achieved by the agents participating in this market.

Within this scene, electricity futures markets emerge as a tool to hedge against pool price uncertainty. Futures markets with electricity derivatives in Europe include:

- Nordpool in Scandinavia (www.nordpool.no);
- EEX in Germany (www.eex.de), and;
- OMIP in the Iberian Peninsula (www.omip.pt).

Nordpool, EEX, and OMIP were launched in 1993, 2001, and 2006, respectively. Hence, the derivative electricity products of ISO New England and PJM markets are traded at the New York Mercantile Exchange (NYMEX, www.nymex.com). NYMEX trading for PJM and ISO New England started in 2003 and 2004, respectively.

In Australia, the exchange group ASX (www.asx.com.au) trades with electricity derivatives. In summary, futures markets provide derivative products (financial and physical) that span from one week to several years and allow consumers, retailers, and producers to hedge against the financial risk inherent to pool prices.

The products available in the futures market include, among others, forward contracts and options:

- A forward contract is an agreement of delivering (consuming) a specified amount of energy in a future time period at a fixed price;
- An option is an agreement for having the choice of delivering (consuming) a specified amount of energy in a future time period. Signing an option agreement involves a payment, denominated premium, regardless of whether or not energy is eventually delivered (consumed).

The futures market organization and functioning are illustrated in Figure 2.5. A producer often uses this market to sell part of its production at stable prices, and conversely, consumers and retailers typically use this market to buy energy at stable prices. Thin arrows indicate the flows of offers and bids, while the thick arrow indicates market outcomes.

2.2.5 Reserve and Regulation Markets

Electricity markets are multi-commodity markets including at least four products: energy, reserve, regulation (load following capability), and balancing energy. Energy is the main product as assumed and explained in the previous sections of this chapter. However, the reserve is an important product that guarantees that enough back-up generation is available in case of equipment failure, drastic fluctuations of production from intermittent sources, and sudden demand changes.

The reserve market is cleared either jointly with the day-ahead market or immediately following it by the independent system operator. It is cleared using an auction algorithm with complexity varying from market to market.

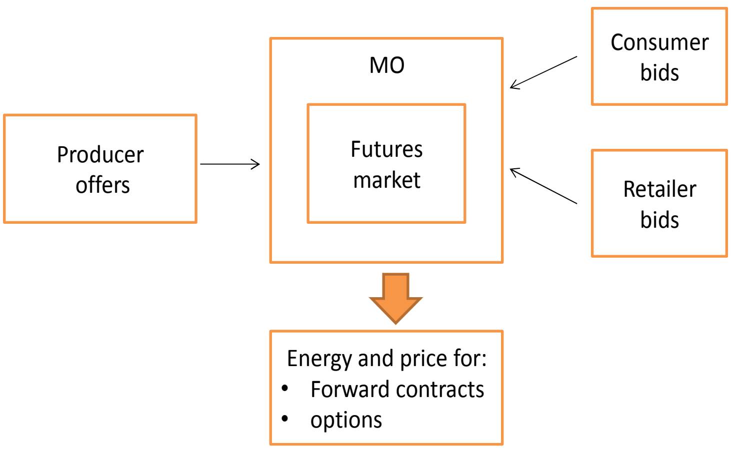


Figure 2.5- Futures market organization and functioning.

Figure 2.6 illustrates the organization and functioning of the reserve market. Mostly, producers provide reserve, but consumers/retailers may provide up/down reserve by reducing/increasing their consumptions. This market ensures a secure short-term system operation in terms of reserve availability. Thin arrows indicate the flows of reserve power (and offers), while the thick arrow indicates market outcomes. In some markets energy and reserve are co-optimized, i.e., they are cleared simultaneously.

The regulation market, cleared several hours prior to power delivery, allocates load following bands among production units with capability to provide this service and interest in providing it. Power bands are allocated based on an auction following an increasing price rule until enough regulating power is attained.

Figure 2.7 illustrates the organization and functioning of the regulation market. Load following capability is provided by selected generation units that can and will. This market ensures that the system frequency is maintained within a narrow band. Thin arrows indicate the flows of regulating power (and offers), while the thick arrow indicates market outcomes.

Since this study considers short-and medium-term horizons spanning, no capacity markets are considered. These important markets are intended to ensure that sufficient capacity (production and transmission) is added to the system so that the market can operate free of rationing due to production scarcity or network bottlenecks, i.e., so that conditions of demand higher than available supply capacity do not occur.

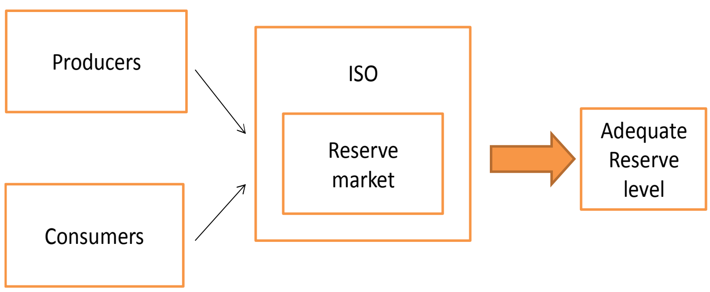


Figure 2.6- Organization and functioning of the reserve market.

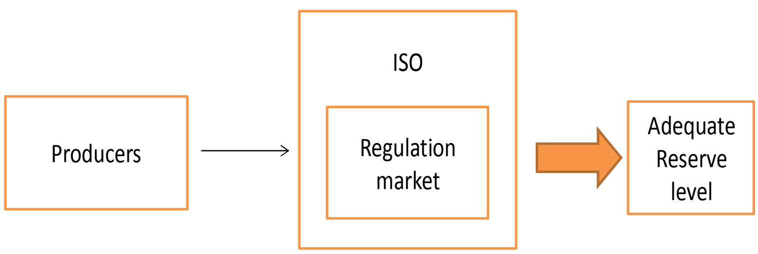


Figure 2.7- Organization and functioning of the regulation market.

2.3 Demand Response

DR comprises some reactions taken by the end-use customers to decrease or shift the electricity consumption in response to a change in the price of electricity or a specified incentive payment over time. DR programs are categorized into two basic groups, called Price-Based Programs (PBPs) and Incentive-Based Programs (IBPs) [10].

Some literature papers named these categories as a system and market-led, emergency and economic-based, or stability and economic-based DR programs [11]. IBP are further divided into classical programs and market-based programs. In classical IBP, participating customers receive participation payments, usually as a bill credit or discount rate, for their participation in the programs.

In market-based programs, participants are rewarded with money or their performance, depending on the amount of load reduction during critical conditions. Figure 2.8 shows this kind of clustering. It should be noted that IBPs are classified into three subsets namely; voluntary, mandatory, and market clearing programs.

Each of these groups consists of several programs. These DR programs are discussed in more detail in [12]. DR programs can be classified as either price-based or quantity-based programs. Price-based programs attempt to reduce consumer energy demand through price signals. Quantity-based programs, on the other hand, attempt to lower homeowner demand through direct utility control of certain loads in the home such as air conditioners, electric water heaters, and/or pool pumps [13].

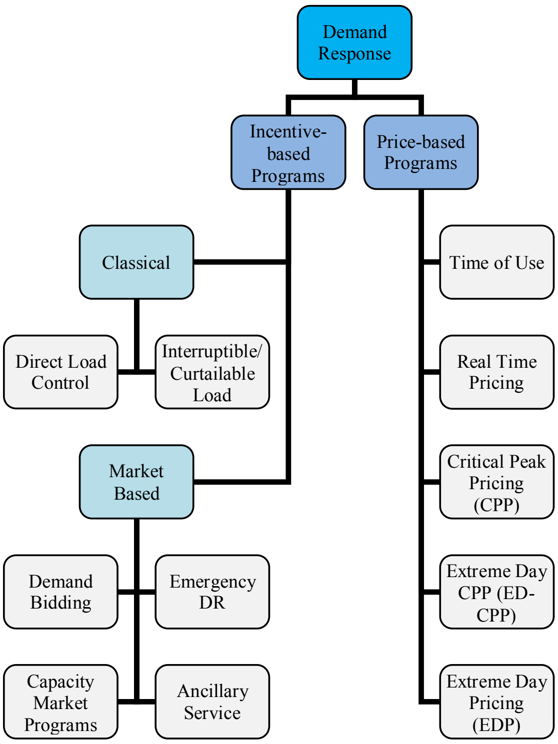


Figure 2.8- Categories of demand response programs [11].

Figure 2.9 demonstrate another kind of clustering. In order to model responsive load, it is used the concept of elasticity of demand to model load reduction and load recovery by participants in DR programs. In this context, the comprehensive economic model of DR programs developed in [14]. In [15] is indicated the necessity of DR programs in providing a flexible load profile. This provided flexibility can potentially increase wind power integration into the grid in a cost effective way. In this thesis, both the priced-based and incentive-based DR programs will be taken into account.

In some reports, definitions and benefits of demand response in power electricity markets are proposed. Authors in [17] proposed a summary of demand response in deregulated electricity markets. The definition and the classification of DR, as well as potential benefits and associated cost components, are presented.

2.3.1 PBDRs Model

Economists believe that acts real price of electricity to consumers will increase efficiency. On the other hand, PBDR or time-varying tariffs applied in the restructured power system improve the demand curve and reduce the load during peak hours. Due to the changes in electricity costs, consumers are encouraged to participate in DRPs. The PBDRs in this current issue include the Time of Use (TOU), Critical Peak Pricing (CPP), and Real Time Pricing (RTP).

In these programs, the electricity tariff varies according to the cost of energy in each time slot. Besides, by applying time-varying tariffs, with higher rates at peak hours, consumers are encouraged to reduce consumption during peak hours or in an emergency and transition to low load hours.

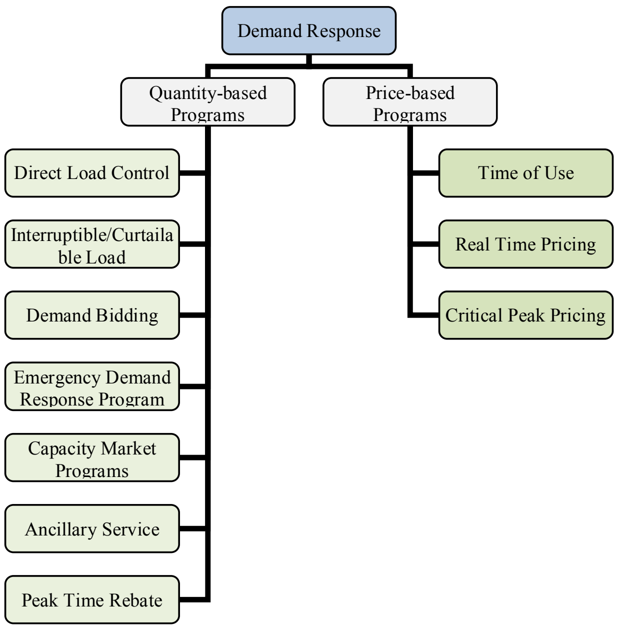


Figure 2.9- Classification of demand response programs [16].

The authors of [18] have gone into detail about these DR programs. The amount of demand-side consumption related to customers who participate in PBDRs in a day-ahead market is derived from Equation 2.1. It is an exhaustive PBDR model based on the "self-elasticity" and "cross-elasticity" concepts of demand to model a plunge in load through the participation of customers in price-based DRPs [14].

$$d(t) = d_0(t)\left\{1 + \sum_{t'=1}^{24} E(t,t').\frac{[\rho(t') - \rho_0(t')]}{\rho_0(t')}\right\} \tag{2.1}$$

where $d(t)$ is the final amount of electricity demand and $d_0(t)$ is the primary amount of electricity demand. $\rho(t')$ is the final amount of electricity tariff $\rho_0(t')$ is the primary amount of electricity tariffs as well. The elasticity of demand side is formulated by $E(t,t')$.

2.3.2 IBDRs Model

In these kinds of programs, an incentive fee is offered to customers participating in DRPs. The incentive amount is separate from the cost paid by customers for electricity consumption. The amount of power consumption incentive may be just credit, payments on preset contracts, or proportional to amount of reduced load. Customers' participation is often optional. However, in some DRPs, a fine of some amount will be considered for consumers who state that consumers will participate in the program but do not reduce their loads in the relevant time. In these programs, a series of incentives is used to encourage consumers to participate in demand response.

Unlike price-based DRPs, the response rates in these programs are not related to the customer reaction to price changes and even other effective parameters such as weather conditions. Therefore, it is not difficult to predict their effectiveness. In order to measure the amount of load reduction to determine the amount of payments to customers, DRPs employ methods for the determination of normal consumption versus their reduced load. These types of programs unlike price-based DRPs (in which predicting and measuring the amount of consumption reduction are difficult), are employed as a useful tool for cost estimation and also maintain reliability through the ISO [19].

The IBDRs in this current study include I/C, DB, ASDR and EDRP. In the Demand Bidding (also called Buyback) method, the major customers submit a load reduction bid to the ISO, and after the market has cleared, if the bid is accepted, the customer is obliged to execute the contract, otherwise fines will be imposed. These programs are employed as the solutions to avoid increasing the market price.

These programs are attractive for many consumers due to keep the electricity prices fixed for customers. These programs are implemented by encouraging large consumers to bid for their purchased energy with self-offers or by encouraging consumers to determine the amount by which they are willing to reduce their electrical power consumption in return for the market price.

The bidding strategy in these DRPs could have the same formulation as in day-ahead and real-time markets. In the day-ahead market, participants in these DRPs can offer the amount of energy reduction on the preceding day and can be involved in optimum operational planning. If their offers are accepted in this market, the participants are obliged to reduce their daily consumption.

If they do not reduce their consumption, they will be charged heavy penalties. This program implements by the New York Independent System Operator (NYISO) using this approach. In another approach, the participants are asked to reduce their consumption, and if they drop their electricity usage, they will receive the money market clearing price as in the model used in NYISO [20].

In the EDRP, participants receive an incentive reward for dropping their load when the system reliability seems to be in doubt. This incentive amount is announced in advance. In such programs, reducing the load is optional and there is no penalty for consumers who do not participate in the program. So after the announcement of the need to reduce the burden, consumers can ignore the incentive fee and not reduce their consumption.

DR programs are modeled based on the customer's benefit function using the price elasticity concept which is one of the most common and powerful methods in this field [21]. Elasticity represents the customer's sensitivity with respect to the electricity price changes as formulated in Equation 2.2 [22]. It is worth noting that the elasticity matrix include both load reduction and load shifting behavior of customers and the elasticity matrix links the power consumption at each period to other periods.

$$E_{t,t'} = \frac{\Delta d_t}{\Delta \lambda_{t'}} . \frac{\lambda_{t'}^{ini}}{d_t^{ini}} \tag{2.2}$$

Actually, the price elasticity of demand is variable due to price and quantity. However, this thesis is not deal with uncertainty of DR and the considered DR model is without any uncertainty. It is a popular assumption for elasticity modeling that has been used in many previous published papers such as [21].

Moreover, the elasticity of demand is an input parameter of our proposed model and obtaining precise value for price elasticity of demand is out of the scope of the current thesis. It should be noted that Time-Based Rate DR Programs (TBRDRPs) have no additional cost or income for the customers since these are usually implemented obligatory by ISOs.

Despite of TBRDRPs, implementation of IBDRPs affect the net benefit of customers due to the incentive and penalty payments in various IBDRPs. On this basis, the net benefit of customer can be calculated as in equation (3):

$$B_t = Uti(d_t) - d_t \, \lambda_t + Inc_t \, (d_t^{ini} - d_t) - Pen_t \left(d_t^{Contract} - (d_t^{ini} - d_t) \right) \tag{2.3}$$

The first term of Equation 2.3 is the customer's utility at hour t as a function of amount of consumption, d_t.

Particularly, the customer's utility indicates the production income for industrial customers, while it is the productivity for commercial demands. The cost of customer's electricity consumption at hour t has been considered in the second term. Moreover, the income as a result of incentive payment and the penalty cost for customers who avoid doing their obligations according to the contract have been formulated through the two last terms, respectively. Note that, Δd_t, it indicates the changes in initial demand as a consequence of DR implementation due to price changes or an incentive payment or a penalty consideration. In order to find the amount of demand in which the maximum customers' benefit is yield, a partial differential equation with respect to d_t is formed as below [21]:

$$\frac{\partial B}{\partial d_t} = \frac{\partial Uti}{\partial d_t} - \lambda_t - Inc_t - Pen_t = 0 \tag{2.4}$$

and therefore:

$$\frac{\partial Uti}{\partial d_t} = \lambda_t + Inc_t + Pen_t \tag{2.5}$$

The most often used customer's utility function is in quadratic form as it can be seen in Equation 2.6 [23]. Equation 2.7 can be obtained by differentiating Equation 2.6 and replacing the result in Equation 2.5. It is worth noting that, $E_{t,t}$ is the self-price elasticity of demand and λ_t^{ini} denotes the initial tariff of electricity before implementing the DR [21]. Hence, the customer's consumption after DR implementation can be formulated as Equation 2.8 for each time period.

$$Uti_t = Uti_t^{ini} + \lambda_t^{ini}\left(d_t - d_t^{ini}\right)\left(1 + \frac{d_t - d_t^{ini}}{2E_{t,t}d_t^{ini}}\right) \tag{2.6}$$

$$\lambda_t^{ini}\left(1 + \frac{d_t - d_t^{ini}}{E_{t,t}d_t^{ini}}\right) = \lambda_t + Inc_t + Pen_t \tag{2.7}$$

$$d_t = d_t^{ini}\left[1 + E_{t,t}\frac{\left(\lambda_t - \lambda_t^{ini} + Inc_t + Pen_t\right)}{\lambda_t^{ini}}\right] \tag{2.8}$$

According to the definition of price elasticity of demand, electricity tariff changes in one period can affect the consumption in the other periods. This concept is known as the cross elasticity. On this basis, the calculated single period model in Equation 2.8 can be extended in order to obtain the multi period model as formulated in Equation 2.9 [21]. Equation 2.9 represents the optimal amount of demand from customer's point of view after participation in DR programs considering given electricity tariffs, incentive, and penalty.

$$d_t = d_t^{ini}\left[1 + \sum_{t'=1}^{NT} E_{t,t'}\frac{\left(\lambda_{t'} - \lambda_{t'}^{ini} + Inc_{t'} + Pen_{t'}\right)}{\lambda_{t'}^{ini}}\right] \tag{2.9}$$

It should be noted that the relation among different time periods is considered directly through elasticity matrix. Therefore, the value of modified demand at each hour may affect by all the other periods as formulate in Equation 2.9 [21].

2.4 The Presence of Wind Resources in the Energy Market

Wind energy is one of the renewable energies which has been increasingly used throughout the world due to its low cost compared to other novel energies and not polluting the environment. Such that wind energy has been had the greatest share (43%) of producing electricity in Europe in 2008 [24]. Effects of wind energy on power networks has been studied from different aspects; it has been compared to conventional energy resources in terms of output power variability and not being controllable which is one of the important challenges in this context.

Non-programmability of renewable energies is a problem for introducing them in the short-term and long term plans for energy production. Considering production uncertainty of wind farm, probable scenarios which are extracted using probability error prediction functions and wind speed information through years, are used for random production scheduling [25], [26].

In [27], next day market clearance considering the uncertainty of wind units with high penetration coefficient is studied. Reference [28] has considered a probable density function for wind power prediction error and has used a mathematical model based on random-compulsory scheduling for calculating optimal spinning reserve in the system; it has also considered load prediction and exit of units in addition to wind uncertainty for calculating required reserve. Monte-Carlo simulation method is used in [29] to evaluate the reliability of power system in order to coordinate wind farms.

2.4.1 Scheduling Wind Farm Production

The output power of wind farms depends on wind speed and turbines. Therefore, speed model and turbine model can be combined to achieve the wind farm model. Using an appropriate wind speed model, a suitable model can be obtained for output power of a wind turbine.

Since produced power of a wind farm is equal to total powers produced by turbines of that wind farm, thus an appropriate model can be obtained for produced power of a wind farm. There is a 3rd order nonlinear relation between wind speed and output power of a wind turbine [30]. In the following equation, the output of wind turbine is expressed mathematically:

$$P = \frac{1}{2}\rho A v^{3} C_{P} \tag{2.10}$$

Maximum output of wind turbine is theoretically 0.59 which means that maximum efficiency of wind power is 59%. In many references including [31], wind speed behavior is modeled based on Weibull probability distribution. Thus wind condition at the installation site of q^{th} turbine can be predicted according to the following equation:

$$h_q(v) = \left(\frac{k_q}{C_q}\right)\left(\frac{v}{C_q}\right)^{(k_q-1)} e^{-\left(\frac{v}{C_q}\right)^{k_q}} \quad , \quad 0 < v < \infty, \forall q \tag{2.11}$$

The above equation describes the behavior of wind speed. Weibull probability distribution function is defined using parameters C_q, and K_q. The last term of the Equation 2.11 states that both parameters can be obtained through regression analysis of wind speed distribution for installation site of q^{th} turbine.

Meteorologists have specified wind speed distribution for a number of wind regimes in the world which are proportionate to wind distribution patterns. For example, in a mild climate, k factor of 2 is a proper approximation. The output power of wind units can be calculated based on the following model [32]:

$$PW_i = \begin{cases} PW_i^{max\frac{v^k - v_{CI}^k}{v_R^k - v_{CI}^k} \; CI\,R} \\ PW_i^{max \; RCO} \\ 0 \quad (v < v_{CI} \& v > v_{CO}) \end{cases} \tag{2.12}$$

where PW_i is the net produced power of i^{th} wind unit, PW_i^{max} is the maximum power produced by wind unit, v is the instantaneous wind speed, v_R is the nominal turbine speed, v_{CI} is the minimum speed for power production, v_{CO} is the maximum speed at which turbine can produce power without difficulty.

2.5 Related Previous Researches

Nowadays, necessity attention to environmental issues, fuel troubles, and economic points of view of applying the conventional sources extremely encouraged decision makers to replace thermal sources by Renewable Energy Sources (RESs) [33], [34]. Different countries have increased contribution of renewable energy resources with a range of policies and incentives [35]. In some countries, wind sources participate in the electricity markets disregarding imbalance penalties [36].

Imbalance penalties are defined as power planned by supplier minus generated power. It is used for security and appropriate utilization of system and avoids to be trifled with market. In some power markets, wind resources will be allowed to offer energy in the market, but some of supportive methods are used to increase their income. These methods usually increase power imbalance in the time of use and thereupon, will follow increasing the cost for the system [37].

Since wind power and other renewable energy are deployed recently, the uncertainties in addition to unforeseen network contingencies cause to systematic changes and serious challenges face to the ISO’s performance. In this condition, innovative and reliable DR approaches results in more flexibility, providing the comprehensive and workable solutions for compensation of the wind units' uncertainty and mitigation power systems concerns. Based on the last investigations on DR programs, it can be found that such comprehensive programs are workable solutions for movement in the direction of increasing the flexibility of the electrical systems [15].

To dealing with the intermittent nature of RESs, an effective management system associated with DRP is required [38]. DRPs can mitigate the risks of taking part in the energy markets for market players; furthermore, improve the reliability and efficiency of the electrical system. Although the participation of customers in DRPs is an advantageous option from system operator’s points of view, it can significantly affect the strategic behavior of generations companies (Gencos), especially in oligopoly environments [39].

Focusing on the incentive-based DR, peak demands can be shifted to off-peak and the cost of system operation is minimized [40], [41]. In these studies, the responsive loads are moved from peak period to off-peak under the ISO direct load controls considering the network limits and in the presence of wind generations.

In some power markets, wind resources will be allowed to offer energy in the market, but some of the supportive methods are used to increase their income [42], [43]. These methods usually increase power imbalance at the time of use and thereupon, will follow increasing the cost for the system [44].

In [45], a changeable tariff method has been used to specify income of wind power plant in the power market. In this method, the cost of consumption rises in proportion to its increase and therefore, more consumption is not associated with more subsidy and high consumption customers are in the focus of rising cost instead of whole customers. In [39] and [40], the method of profit maximization is used to participate wind power plants.

Modeling of uncertainties is necessary for these methods. Since the interval between the time of bidding and time of use may be high, wind power plant’s income will be reduced by these methods. A supportive method for the participation of wind power plant in the power market has been presented in [48]. However, if the content of wind resources increases, use of supportive methods will be inefficient.

Appropriate values for parameters estimation of this probability function accepted for wind speed have been given in [49]-[52]. In [53], using the game theory, make decision strategy for bidding price of selling electricity in an oligopoly electricity market at day-ahead energy market for wind power plant owners has been presented.

In [54], the goal is to achieve a flexible, secure, economic and clean network with the flexibility in supply side and demand side that the DRP has been used for the flexibility of demand side. In [25] and [48], a stochastic decision-making model has been presented for the participation of wind energy suppliers in a competitive market at three levels of day-ahead, intraday and balancing markets.

Reducing the period of uncertainty around wind generation and allowing WPPs to adjust their offers more frequently are main potential benefits of sub-hourly energy markets such as the intraday [56]. A flexible load following concept is proposed in [57] with the aim of satisfying a multi-objective problem. The load follows the wind farm output to satisfy objectives, such as available transmission capacity maximization while minimizing losses.

In [58], an offering optimization model for aggregated wind power and flexible loads in the day-ahead market is suggested. The flexible load is considered as a storage unit that can cover wind fluctuations and reduce imbalance costs of WPP. The only uncertainty source presented in that paper is wind power generation, while WPP's risk is not considered. In the 24th wind task of the International Energy Agency (IEA) that investigates issues, impacts, and economics of wind integration, DR was introduced as the most flexible and cost-effective option to facilitate the integration of wind [47].

In [59] authors are proposed the review paper and are scrutinized the latest DR definition and classification which is used in this thesis. The impacts of uncertain wind power and demand response on power systems operation and power market clearing have been studied in [60], [61].

This thesis focuses on the impacts of wind generation and demand response on the day-ahead market clearing. As the state-of-the-art market clearing mechanism uses deterministic UC/ED models, the deterministic NCUC model will be adopted in this thesis to keep consistent with the current power market practice.

Load shifting consumers will enroll into the incentive-based DR programs for declaring their load shifting capabilities and receiving financial incentives for providing such flexibilities[62]. For instance, certain industry loads could shift their production activities from daytime when electricity prices are high to evening with lower electricity prices.

The problem is formulated as a mixed-integer linear programming (MILP) model to study the impact of demand response and wind generation. The electricity market is performed as an oligopoly market rather than a perfect one, due to some reasons, such as transmission constraints, the effect of loss on electricity price, and a limited number of Gencos. Moreover, the structure of the market and its operating rules might affect such procedure, to a great extent [63].

The uncertainty of the market generation power resulted from the uncertainty the wind generation power is modeled by stochastic methods. Another source of uncertainty in this problem is the clients' demand which is considered via scenario generation method.

The proposed method is formulated as a bi-level stochastic programming problem. One of the problems complicating the ISO or generator's decision making is the uncertain parameters that affect its decision condition or its profit. Two major sources of uncertainty in this problem are pool prices and clients' demand [64]. The uncertainty of these parameters would affect generator's profit as well as decision variables. The methods of modeling the uncertain parameters are probabilistic. In the probabilistic approach, the Probability Density Function (PDF) of the uncertain parameters is used to obtain the PDF of the objective function [65], [66].

The probabilistic methods provide a good sight about the optimization problem but the computational burden is increased for the problems with a large number of uncertain parameters [67]. Modeling the uncertainty via scenario generation is widely used in power system studies, among non-probabilistic methods [68], [69]. In the literature, several methods have been proposed such as using demand response programs in the agreements with the client [70].

Modeling methods of the market players' behavior have structural differences for price-taker and price-maker Gencos. Since the price-maker Genco's behavior influences the market price, analyzing the behavior of other competitors seems necessary for this process. The game-based method has been widely used for the modeling of price-maker Gencos behavior. According to the level of competition, these methods could be categorized into Bertrand, Cournot, and supply function equilibrium (SFE).

The problem for price-taker Gencos is simpler because the market price is approximately independent of their bidding strategy. In this method, other participant's behaviors are modeled via market price forecasting [71], [72]. Price forecasting inaccuracies on short-term operation scheduling of Gencos is studied in [73].

In this sense, uncertainty modeling methods need to be implemented since the generation dispatches and the profit of the companies are very sensitive with respect to the forecasted day-ahead price. These methods can be classified into stochastic and interval-based methods. In the probabilistic methods, probability density function of the uncertain parameter is used in the maximization of the expected profit of Genco [74].

Simplification assumptions of stochastic methods make them capable of handling large problems. The interval-based and scenario-based optimization methods are the two important uncertainty modeling categories, which are employed in the context of the presence of renewable energies. The scenario generation methods simulate the day-ahead price with various numbers of scenarios and try to cover the most probable states [75]–[77]. The risk of uncertain parameters is required to be taken into account for deviation from their forecasted value.

The variance of profit, which is more suitable for probabilistic methods, is incorporated in the objective function of the self-scheduling problem of a price-taker Genco in [78]. Unlike the scenario-based methods, these methods have no assumption on the density function of uncertain parameters and instead of introducing the probabilistic measure of risk; they guarantee a specified level of profit, which is more user-friendly.

Participating in hybrid markets of energy and reserve is investigated in [55] and [56]. Moreover, the effect of bilateral contracts on competition strategy of Gencos is investigated in [57] and [58]. The day-ahead electricity market condition will be more complicated In the presence of the renewable generation sources and DRPs in demand side contracts. In this situation, the day-ahead bidding curve and selling prices need to be determined simultaneously.

Due to the increase of energy consumption and environmental conservation concerns and a decrease of fossil fuel resources, penetration of renewable resources has significantly grown throughout the world. Among the renewable energies, wind power assigns a considerable share of the generation portfolio.

Government subsidies, tax exemption, and market-based and nonmarket-based support schemes are various solutions that have been designed and implemented to support Wind Power Producers (WPPs) in different countries all over the world. Nevertheless, it seems that providing an appropriate context for the participation of WPPs in a competitive electricity market to achieve profit through a market mechanism is the best way to encourage and support WPPs.

Because of limited predictability and associated uncertainty of wind power, WPPs are unable to compete with other market players unless a suitable condition is provided for them. Successful market integration of wind power will require efficient market designs. Several research works have been published to improve the performance of WPPs in electricity markets. The publications can be categorized into three major approaches:

- Improving market rules, regulations, and structures;
- Improving uncertainties' modelling accuracy;
- Utilizing other technologies and facilities besides WPPs.

A large amount of previous research has considered the structure of two conventional electricity markets: 1) DA; and, 2) balancing markets. In these works, scenario based stochastic programming approaches have been used from the WPP's viewpoint to maximize its profit. Uncertainties in wind availability and market prices are taken into account using scenario generation techniques.

However, only a limited number of papers have considered a different time horizon and sessions market mechanism that allows being reduced the uncertainty of the forecasted generation of WPPs before delivery time in order to reduce imbalance costs and increase expected profit [47].

In this work, improving the problem formulation would be accomplished by reducing the uncertainties of WPPs compared with other market players. Despite undeniable advancements of wind power forecasting, the DA forecasts can cause the uncertainty of power system to increase. Changing the periods of wind forecast from DA to different time horizon and sessions of the market such as intraday or real-time market can decrease forecast errors drastically.

Allowing WPPs to react to the latest information gains (i.e., more accurate wind forecast) is the key to improving the market design and facilitating renewable energy resources' participation in the electricity market.

Different time horizon and sessions of the market have positive impacts on both producers and operation of power systems. Corrections needed after day-ahead gate closure can lead to a reduction in volume and price of real-time balancing market and allows electricity markets to benefit from the integration of wind energy.

Utilizing DR to compensate wind generation imbalances can reduce the uncertainty of power system. An efficient integration of intraday markets allows market players to react to the latest information (e.g., more accurate wind forecast). Creating a platform that allows demand response resources (DRRs) to contribute to the intraday markets improves both WPPs business and power system flexibility.

DR technologies face low costs for providing intraday and balancing services, especially for positive balancing power such as load reduction. At present, strict rules prevent the large potential of demand response resources (DRRs) for engaging in intraday and balance markets.

Also, only day-ahead market provides a sufficient incentive for DR participants. However, using DRRs ensures the physical flexibility within the system. Moreover, the formation of liquid markets closes to delivery such as the intraday markets guarantees that this flexibility will be accessible for those who need it.

Hence, in the current thesis would be investigated the impacts of the full flexibility that DRRs can offer to limit cost growths due to wind uncertainty. Due to the considered mechanism for imbalance penalties, as explained below, the excess of wind power partially reduces WPP's revenues, while in cases where the shortage of wind power occurs a cost is imposed on WPPs. Therefore, decreasing the amount of negative imbalances seems more crucial.

In this situation, in intraday time scales, demands can adjust their consumption to compensate the deficit of wind power through load reduction at a given amount of payment. This problem would be modelled in terms of demand response exchange (DRX) market. It should be noted that, by considering the DRX market, the first and third above previous approaches are taken into account together. The objective of WPPs while attending the market is the maximization of their profits considering the entire operation sequences, DA, intraday, and balancing markets.

More uncertainties that make more scenarios increase the calculation's volume. Despite the high calculations, Monte Carlo Simulation (MCS) method is selected in most cases for making desired scenarios because of straightforward and high accuracy. But, the optimization methods used in such papers are the evolutionary optimization methods and have its own disadvantages such as local minimum trap and the need to combine multiple algorithms or dependence on initial conditions and lack of guarantee good result.

Also, by combining the impact of a variety of demand response programs in such a network in the presence of wind resources, that this diversity of demand response program rarely already used in any articles, based on the best behavior of suppliers and their price bidding, the best demand response program and subsequently most flexible condition of market in the shortage of generated powers of renewable units or increase the consumption power and imbalance of supply and demand would be selected.

A model will be proposed for short-term scheduling with demand side management. In fact, system uncertainties including an outage of wind generation sources and implementation of demand response programs are merged in a two-stage stochastic framework for the optimum operation of the network system. For increasing the network security and decreasing the operation cost, a demand response model is considered.

Also, an optimal electricity market design is presented for scheduling of thermal and renewable energy producers as well as demand response resources. Uncertainties related to renewable energy forecast error and consequently generation outage power are modelled through scenario generation.

Then, with regard to trading floors among: 1) day-ahead; and, 2) balancing markets and so on and taking into account the relevant constraints; the thermal unit commitment problem is solved considering wind energy injection into system. It is expected that the DRPs can improve the market efficiency especially during peak hours when thermal Gencos become critical suppliers and the combination of DRPs and wind farm can be so efficient.

Moreover, the effects of the DRPs on the behavior of electricity market players in the day-ahead energy market will be modelled in presence of renewable energy resources. In such environment, the market transactions are cleared by means of a security constrained unit commitment problem.

It is expected that the numerical results with the presence of renewable energy resources indicate that different types of these DRPs differently affect the behavior of market players that should be studied by the system operators before their implementation. Using MCS method, several scenarios are generated to show the possible contingencies in day-ahead energy market. Then, a scenario reduction method is used for reducing the number of scenarios.

Chapter 3

3. The Mutual Impact of Demand Response Programs and Renewable Energies

3.1 Introduction

Renewable energies due to the green future power system target and DRPs as well have always been a key research area. However, the intermittent nature of such kinds of energy power may impose some technical and economic challenges to ISOs besides DRPs as the acceptable effective solution may increase the need for additional investigations. Motivated by this need, this chapter focuses on the review of the latest researches in these cases to be an extensive reference for the future works.

3.2 Framework

Renewable generation technologies have been promoted by policy makers throughout the years in an effort to increase the sustainability of the electric power systems. The intermittent nature of the wind and photovoltaic resources make them difficult to predict. Over the past years, wind power has been one of the fastest developing clean technologies, reaching a considerable penetration in electric power systems.

The intermittent nature of this type of generation and possible unforeseen variations in power over a short period of time are caused by serious challenges. Such concerns on climate change, energy security and price changing frequently resulted in many power systems have started changing their energy generation portfolios to include significant amounts of renewable energy resources [83].

Although most renewable energy resources have a considerable installed capacity growth in the recent years, the development of wind power has enhanced much more, especially. Generally, the wind and solar PV are the most mature forms of renewable energy and are integral to our clean energy strategy [84].

The majority of decision makers, power system operators or investors have focused on the advantages and challenges of proposed DR schemes that set specific goals. Therefore, motivated by this requisite, this chapter focuses on the literature reviews of recent reports of the DRPs associated with renewable energies and the both positive and negative aspects of DR schemes. However, short notice has been taken of DR systems from this point of view.

In [17] is proposed a useful summary of DR, benefits and cost items which are expanded in this current study as well, the number of indices for DR evaluation in the electricity market and the impact of DR on energy prices employing simulated case study. Nevertheless, the investigation is conducted in any renewable energy. A review manuscript is submitted in this context.

The most recent review on the subject has been published, with a more narrow scope in comparison with this paper is [59] followed the previous one added successful and effective implementations of DR in the world, whereas here we strive for a broader report of the wide-ranging topics. Only a few references included renewable discussions are reviewed and an in-depth and detailed investigation are not performed in this regard.

This research is now the main focus of attention to contribute to sealing this research gap and emphasizes the current problems and challenges important for future plans. Moreover, investigation on various electricity market designs enabling demand response and renewable energy systems and the system of recent studies classification taking into account the both role of renewable energies and DR programs into their proposed optimization methods in various kinds of the energy market is performed.

Reference [85] is presented a review of system flexibility measures in the energy systems of high variable renewable electricity. They claimed to observe that the flexibility of the majority of electrical systems can be handled by the system itself without the need to noticeable changes or further investments. In [86] a review of real-time energy markets with distributed energy sources and DR are presented. The valuable real-time market experiences in some parts of the world are explained.

The main objective of this report is to conduct an extensive and thorough review of recent studies on the DR programs in power systems associated with the renewable energies and specifically wind energy and to explore for an appropriate instrument to be the best way of helping system operators. The acceptable solutions are presented in this context to mitigate the electricity market under the mutual effect of DR programs and renewable energies with a discussion on advantages and disadvantages of the DR systems.

It is presented a systematic review to improve electricity system flexibility to enable high levels of renewable energies. Besides, in order to address the gap between renewable energy development and DRPs, issues and strategies associated with these two core and fundamental concepts are represented as well and analyzed in this chapter.

In this context, is looked for solutions that are linked to the demand side, electricity power system, power supplies, and the electricity markets. The literature on individual measures, strategies or technologies for electricity system reliability is extensive. In [87] the strong contributions of DR on enhancing system reliability are made during 2014 North American in PJM. The qualitative analysis in regard to benefits of the DR is proposed.

This chapter presents an overview of recent researchers on DRPs and renewable energies. It starts with a kind of categories from previous reports, followed by explanations of different markets and an in-detailed classification of recent relevant literature and benefits and costs of demand response implementation.

3.3 Classification the Solutions for System Operators

Uncertain characteristics of renewable power compared to other conventional plants may pose serious challenges to power system operation. Highly unpredictable nature of renewable power may lead to system reliability endangerment as well as higher operation costs. On this basis, a challenge that system operators are facing with large-scale integration of wind power is how to cope with and mitigate the wind variability and forecast uncertainties.

To address the mentioned challenges, several different studies have conducted on large-scale grid integration of wind power and other kinds of renewable energy. In this regard, providing a more flexible power grid is a common aim that can be seen in all previous reports. To achieve that aim, several solutions are presented for power system operators in former publications which can be clustered around three major categories:

- Utilizing energy storage technologies;
- Providing additional reserve capacity throughout electricity market and improving market mechanism, rules and structures;
- Using flexible demand side resources.

These solutions for power system operators to provide a more flexible power grid are illustrated in Figure 3.1.

3.3.1 Using Energy Storage Technologies

In a tremendous share of the literature utilization of a storage device alongside wind farms or other renewable energies has been suggested. In [88] authors review various storage systems for wind power applications. Particularly in [89], thermal energy storage is reviewed with phase change materials (PCMs) but in building the application.

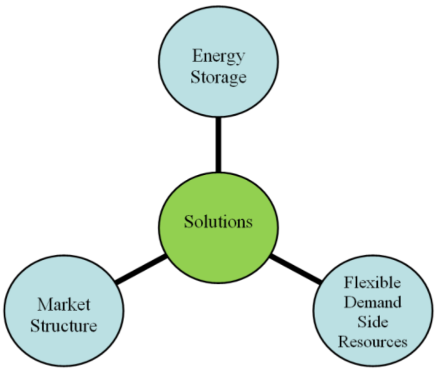


Figure 3.1- Solutions for power system operators to provide a more flexible power grid.

In addition, in [38] since changes required in operational practices for storage plant at different installed wind capacity levels explore the challenges that private storage plant operators will face in generating appropriate bids in a market environment at high variable renewable penetrations.

From reference [38], the authors have tried to improve the efficiency of storage plant dispatches at high variable renewable penetrations, but further research is required, particularly for high renewables scenarios. Achieving efficient dispatch strategies in the systems with high penetrations of variable renewables are highly complex however they plunged into exploring, but the number of scenarios considered is limited.

Authors in [90] assess the value of integrating Compressed Air Energy Storage (CAES) into the future sustainable energy systems with even higher shares of fluctuating renewable energy sources. The Danish case is evaluated in a system-economic perspective by comparing the economic benefits achieved by improving the integration of wind power to the costs of the CAES technology. The result is compared to various other storage options.

A bi-level optimization model is presented in [91], which proposes a look-ahead technique to optimize a merchant energy storage operator's bidding strategy considering both the day-ahead and the following day. Determination of the optimal location and size of storage units have been widely studied.

In [92], a three-stage method is proposed to determine near-optimal locations and sizes of storage used for spatiotemporal arbitrage. Also, applying a hydropower plant as a supplemental unit beside wind farms is another solution which is taken into consideration for reducing the intermittent impacts of wind generation [93].

3.3.2 Improving Market Structure

Another set of papers has proposed new market structures to facilitate wind power integration. The market design and processes have become more complex because of the introduction of new products and services to deal with the variability and intermittency of renewable resources.

In response to these issues one particular market design has been proposed, which is based on the two-part pricing concept [94], and involves the use of standardized contracts [95] to procure capacity for provision of energy and reserves. In this formulation, the ISO contracts with and compensates the market players for making their capacities available in the day-ahead market while paying them a performance payment based on actual production in the real-time market.

In [96] are discussed some key feature of the short-term adjustments required by wind energy and the necessity of intraday markets. In this section the forecast quality and the need for flexibility in the system due to wind energy in five EU countries and quantifies the influence of a "theoretical market coupling" Is evaluated and compared.

Based on [96], the latter analysis shows that a further integration of EU Intraday-Markets can significantly reduce the amount of flexibility needed to compensate for forecast errors. The obtained results of two cases have been outlined in [97] which investigate policy and auction design for energy and reserves to facilitate wind integration.

Other studies such as [98] investigate additional reserve capacity requirements for reliable grid integration of wind power through electricity market environment, belonging to the second category. In [99], authors construct, fit, and validate a hidden Markov model for predicting variability and uncertainty in generation from distributed photovoltaic systems.

Moreover, it was proposed a model that can be used as a tool for planning additional reserve capacity requirements to balance solar variability over large and small spatial areas. It is worthy to note that, application of deterministic approaches in wind-thermal scheduling problems is not effective due to the stochastic behavior of wind generation. Hence, many recent papers focused on stochastic programming approaches as it has exerted in [99],[100].

3.3.3 Using Flexible Demand Side Resources

The third group of the literature includes flexible demand-side resources such as Plug-in Hybrid Electric Vehicles (PHEVs) and Demand Side Management (DSM) solutions particularly demand response. Electric Vehicles (EVs) have been proposed as an option to alleviate the diversity between the electricity supply and demand in systems with high penetration of wind power as emphasized in [101], [101]. The PDFs of the load are generated in addition to the unpredictable power resources such as wind power generation or charging demand of electric cars [102].

In [103] is proposed a novel power management strategy to cope with the inaccuracy and uncertainties of the terrain information with the aim to improve battery life, while maintaining overall system performance. First, the impact of terrain inaccuracy on battery life and system efficiency is analyzed based on two different hybrid energy storage systems with semi-active topologies.

Then, a power management control strategy is developed that actively distributes the power between battery and super capacitor with adaptation to terrain inaccuracy and uncertainties. In addition to EVs, some papers investigated the major role of DR in compensating wind power uncertainties. The possible impacts of DR on power system operation with high penetration of wind power have been analyzed in [104].

Many types of research have been examined to detail the impacts of DR on wind integration. The authors in [105] propose model predictive controllers for real-time pricing problems of electric power systems composed of consumers, suppliers, wind farms, generators and an ISO. They formulate such real-time price optimization problems as model predictive control problems and then demonstrate the effectiveness of the proposed method by numerical simulations.

The drawback with this work is that the DR program used in this reference only provides load reduction. Authors in [106] have gone a step further by considering load reduction as well as load recovery using the self and cross price elasticity concept.

The above-mentioned studies use deterministic approaches while wind power has a stochastic nature. Moreover, quantitative metrics have not been addressed for the concept of flexibility in the literature. Most of the flexibility studies are based on multi-temporal simulation of power system operation.

In other words, a detailed simulation is required to calculate the mentioned metrics, in order to analyze and estimate the flexibility level of a system. On this basis, [52] presents a two stage Stochastic Network Constrained Unit Commitment incorporating DR (SNCUCDR) with application to wind power integration in which various types of voluntary DR programs are also taken into account. It has just discussed only voluntary DR programs that could go for the other DR programs as well or would be doing in future works by others.

3.4 Various Electricity Market Designs Enabling DR and Renewable Energy Systems

The arrangement of the European electricity markets, based largely on day-ahead spot markets, leads to considerable demands for balancing services and/or intraday trading to face with extra amounts of wind-generated through producers. How the electricity market plan in the countries could and should be modified to the complicated and difficult situations occurring due to wind energy. The impact of wind energy on market prices on the variety of markets such as day-ahead and intraday markets have been the main topic of many papers, including [85], [107], [108].

Therefore, the question of acceptable and proper market design has been frequently studied, particularly through [109]–[112]. The majority of these contributions captured the attention either into the spot market or the balancing market. A noticeable exception is [112], it is simulated thoroughly the linking and relating between the intraday and the balancing market.

The fundamental aspect focused on this section is the liquidity under the wide range of the variates of market designs, for spot and for intraday markets as well. The general aim of any improvement to becoming better and achieve the better conditions in market design should be an enhancement and recovery of the efficiency of the markets.

Many methods may be developed to explore this issue: equilibrium investigation in the style of [113] to control and influence price directly and patterns in a oligopolistic model, game theoretical modeling to evaluate the ability incentives for mitigating the market power or simulation studies in the vein of [114] to examine market revenue and costs.

According to previous studies, a kind of classification is proposed in this chapter in Figure 3.2 to improve the operating of the intraday market and therefore make less severe the integration of wind power.

Figure 3.2– Classification of improving the functioning of the intraday market.

The aim of all illustrated measures in Figs. 3.2 is easing the intraday readjustment for wind energy generations and therefore to reduce the cost. The first alternative among 4 options would effectively promote some developments in comparison with the current condition and circumstances, while is not very balanced with the most often working hours and would promote trading costs. In the spot auction, change the closure time for instance to 06:00 p.m. on the day before.

The second option sounds as though beneficial since it would prepare the ground of market for all participants to clear their open positions like they happen, even sooner physical delivery. This debate is reasoned if only constraints in liquidity are not included. In the British experience point of view, this alternative is roughly not very pleasing. It is likely to lead to a reduction of liquidity and consequently to push up the costs which are paid through wind Gencos. The third option is a beneficial compromise as well, along with flexible intraday transaction and bundling liquidity through announcing auctions in the intraday market.

The fourth option would force limitations on the economic performances of the market players. Nevertheless, this would be advantageous for liquidity. However, the advantages of the fourth option are not so obvious. In the power systems with thermal units, renewable energy sources and demand, participants may officially rectify their imbalances.

When some formalities are imposed on the market, the players may submit their transactions bids with the same prices. Therefore, compulsory bids into the intraday market cannot work alone and might be not enough to promote the conditions for individual and independent wind energy generators.

3.4.1 Spot Markets

Power exchanges subjects have become an indispensable tool for both power system operators and demand side investors recently to find the best way to reach their goals. According to [111], less than 25% of all energy electricity consumption is exchanged at the spot markets in the most of the countries.

In the German market, the products at the day-ahead market which range for the following day are traded on the European Power Exchange (EPEX Spot) in Paris. Trading happens in daily auctions. Participants make their price offers to trade electricity until 12:00 am to deliver in every hour of the next day. After gate closure, the whole of offers is employed to make aggregated demand curve and supply curve and consequently a uniform market price [115].

In day-ahead markets, participants prefer the situation in which market prevent from spreading and scattering liquidity in single trades happening over the whole trading length of time which are for instance two days in the UK. Besides, they opt for single auctions. While the volume of the buying and selling in auctions has increased, liquidity in the trading has reduced. The participant's favorites to choose such a kind of auctions and also the changes in auctions may be clarified through the planning process in the utilities.

In different groups of recent studies spot market is employed to cover the supply disruption by using a game theoretic model to reduce the loss caused consequently [116]. In [117] is presented a bi-level approach to optimize the spot-market operations. The solution is employing stochastic approximation to maximize the profit of communicating with close neighbors in the electricity spot market.

3.4.2 Intraday Markets

Expanding wind power production, day-ahead schedules have to be updated in terms of new data arrival. Unit outages and changes in load estimation are included in the new information. Simplifying the problems such as linearizing bidding curves in intraday markets leads to adjustment of impractical plans resulting from spot markets.

In this field, intraday markets can be defined such as markets that are operating between the time after which plans are submitted to the system operator and no longer time be changed. Very low volumes of the energy traded in European intraday markets [111] may explain the probable inappropriate design of the market or untrustworthy market structure. Nevertheless, a closer look at various markets behaviors is required.

3.4.3 Balancing Markets and Reserve Markets

The absolute guarantee of demand-supply balance has always been discussed as the main subject in the literature. Reserves have always been employed in this regard. When the activities of Gencos on the supply side are suspended, the system operators impatiently demand on the reserve markets to provide consumers with balancing in real time through delivering reserve capacity service to them simultaneously in the same market with the costs to a number of imbalances.

As a result, different researches have been carried out to develop the various models for the pricing of these balancing services [107], [110], [118]. Transmission companies (Transcos) use reserves capacity to reduce the imbalances in real time. The major issues for the integration of wind energy may be the amount of reserve and its price.

In [115] the control reserve power markets is defined. According to that for Germany, control reserve powers are traded in Primary, Secondary and Tertiary reserve power markets. Reserve capacities and prices included in bidding offers submitted through Gencos and bought and sold on the control reserve markets.

Reserve capacities have a wide range of the length of time that they last, from four hours to seven days. Different strategic bidding on control reserve markets to maximize the generation's profit and the simulation methods to analyze the effects occurring and happening to prices resulting from the unit's bidding strategies.

In European countries, the primary market is cleared first, after that, secondary and tertiary markets are cleared respectively. The day-ahead spot markets clearance is applied after the auction for reserve. Therefore, past market results varied from market to market can take into account from the decision maker's point of view. In [119] is presented the mathematical form to assess the resemblance manner among different markets or various intervals in an electricity market which can be a helpful multi-purpose tool in such fields of study as well.

Due to investigating recent studies to find the advancing frontiers of the combination of the two subjects of renewable energies and demand response programs in the current studies, Table 1 explains the classification of the proposed optimization models considering different types of market exchanges. Moreover, the direction and track process of researchers can be derived from this table.

3.5 Various DR Costs and Benefits

Recently papers have discussed the positive and negatives aspects of DRPs implementation. In [106] are explained a planning tool to project the expected cost and benefit of DR programs. It allows engineers to run various distribution models, import data from commercial tools, visualize the results, and collaborates through a web interface.

The DR model can simulate TOU, CPP, Peak Time Rebate (PTR), and Direct Load Control (DLC) programs for the purpose of cost-benefit analysis (CBA). It uses the Price Impact Simulation Model (PISM) to estimate changes in system load profiles based on changes in incentives.

The model calculates Net Present Value (NPV), payback period and benefit-to-cost ratio across a program lifetime. This section covers and discusses both potential benefits expected from DR programs and the associated cost.

Table 3.1-Taxonomy of different markets and relevant literature.

Ref.	Day-ahead market				Intraday market	Balancing market	DRX market
	Two-stage	Multistage	Robust programming	Chance constrained			
[120]		✓			✓		✓
[121]		✓			✓		✓
[122]		✓			✓	✓	✓
[123]						✓	
[124]		✓				✓	
[125]		✓				✓	
[126]		✓			✓	✓	✓
[127]	✓				✓	✓	✓
[113]	✓				✓	✓	
[128]	✓						
[129]						✓	
[130]					✓		✓
[131]			✓				
[126]	✓			✓			
[132]	✓			✓			
[133]		✓		✓			
[134]				✓			
[135]	✓		✓			✓	

3.5.1 DR Benefits

Several studies have described the advantages of DR in energy systems with renewable energy resources. In literature [136] analysis and evaluation of benefits of user's demand response are conducted under the smart distribution network. They have established the relevant evaluation index system. In order to reflect the real benefits of each index more realistically and effectively, each index of different subject covers the definite and interval data.

Under different matching mechanisms, a numerical example evaluated synthetically on the benefit of the demand side resources with wind and light as the main body. Simultaneously, matching combinations with optimal demand side resources are selected. According to [137] due to run payment to renewable energy producers, it is better for the micro grid to have no load and acts as a generator and investors, therefore, purchase separately their required energy from distribution network by their own revenues.

For the optimization program, an objective function from the micro grid manager's viewpoint is extracted and is maximized using particle swarm optimization. In Figure 3.3 [17] is summarized the benefits associated with DR; the benefits associated with DR are clustered around four main collections: participant, market-wide, reliability, and market performance benefits.

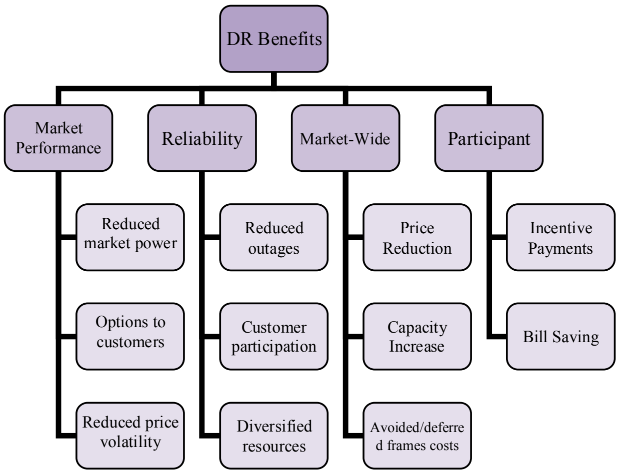


Figure 3.3- Classification of DR benefits [17].

The benefits of DR programs are not only for the persons getting involved in programs; some are market-wide. An overall market price cutting is anticipated eventually due to a more gainful employment of the infrastructure, for instance, a decline in the demand for the units with expensive electricity generation. DRPs exert a powerful effect on the pushing down the market prices [15], [138].

Furthermore, DRPs through incentive-based programs can expand short-term capacity which in sequence, leads to keeping down the capacity costs. Reliability is considered as a subcategory of the DR benefits because it affects all market. Due to the importance of reliability, it is considered as an individual category. Through an accurately modeled DR program, participants can help in decreasing the risk of outages. Consequently, participants are diminishing the risk of being faced to enforced outages and/or electricity interruption.

According to [3], [139], it can be concluded that the last subcategory of DRPs benefits is boosting electricity market performance. There will be more opportunity for participants DR program to have more alternatives in the electricity market even though retail competition will not be available. Participants can reduce their consumption since they can make an impact on the market, especially with the IBPs and PBPs.

One of the market performance enhancements is the cut off price changing frequently in the spot market. DR programs, particularly for heavy consumers, help to bring down the costs of system operating as a result of this action drop the market prices [86]. Since large-scale producers may have control over the market, implementing the DRPs or taking part of consumers in such those programs mitigate the market power. The role of power generators as price makers in the market underplays through demand responsiveness and consequently, the considerable drop appears in the market power indices [39].

Under environmental benefits discussions, DR programs and also renewable energies are always the advantage keys for these concerns and contain gainful land employments thereby averted or delayed new electricity infrastructure such as power production units and power transmission or power distribution lines

Environmental quality improvement by reason of effective and optimum use of resources; and prevention of depletion of natural resources which in recent years become a major focus of governments, organizations and researchers [16]. In [59] was assessed DR benefits in seven categories: economic, environmental, market efficiency influences, pricing, customer services, lower cost electric system and services, risk management, and reliability.

3.5.2 DR Costs

Every DR program includes variant types of costs; Figure 3.4 depicts a clustering of DRPs costs, where both DRPs implementers and participants at demand side suffering from initial and running costs [18]. The participants might require buying some new or digital technologies, besides install to take part in a demand response program: intelligent thermostats, controlling of peak loads, energy management systems, and production units in place.

A set of response decisions as a plan or strategy requires being scheduled therefore it can be implemented as an event. These basic and primary costs are usually paid by the participant; nevertheless, technical assistance and other paraphernalia should be supplied through the program.

Customers running costs are those related to events. Based on the DR plan, these costs may be different. One of running costs which imposed to participants is an inconvenience. Sometimes the thermostat must be turned off through the customers and then on again when it does not work correctly.

Other relevant costs are lost business that can be considered as business integration. Rescheduling of industrial processes and activities can be clustered which is referred to the last running costs of participants. If a customer who is involved in a DR program employ a production unit in place as an onsite generation unit, operating and maintenance costs or for example fuel cost should be considered.

The DR operator has to decide base on initial and running wide costs of the power system. Metering and communication frames and structures costs are included in the majority of DRPs in terms of initial costs. Advanced smart electricity meters to read and measure the amount of energy usage at particular time intervals, for instance, hourly for real time pricings should be employed through demand side participants.

It would be considered to involve the administration and management costs of the program into the running costs of DRPs. In addition, incentive payments are assumed in terms of a portion of the running costs of the DRPs providers.

Before employing the large majority of DRPs improving the billing system is essential. The primary cost item before employing any DRPs is effectively teaching in general suitable and acceptable customers about the profound helpful effect of the program.

Different DRPs alternatives should be described to participants and also response strategies should be properly explained. Participant educations make a considerable impact on DR program success. Effective marketing proves a great value to draw new participants and tempt them into taking part in programs. Moreover, a comprehensive evaluation and accurate gauge of DR programs are main to implement a practical approach to achieving the intended purposes of the programs [18].

From another point of view, DR costs are well explained and defined in terms of two groups. The initial implementation includes program design, marketing, metering communication and business integration. Besides, incentive payments, administrative and maintenance, customer opportunity are included in the second group [59].

In general, costs arise for two parties: the industrial business that delivers Demand Response and its provider or another party that creates the infrastructure need to support Demand Response [18]. Due to [140] Costs for DR program operators are subdivided into three specific categories as observed in Figure 3.5.

In summation, it is depicted that variable opportunity costs are the primary and main type of cost, while investments and annual fixed costs are too slight or small in amount to be of importance. The results of an advantageousness calculation illustrate that DR can be economical:

<u>Investments</u>: To expand Demand Response capacity through implemented DRPs, several worthwhile investments have to be promoted. Measurement and communication infrastructure and control advanced technologies should be installed [141], [142].

Moreover, enterprise software should be developed with the aim of achieving the enabling of the load control. This type of costs depends on the kind of the DRPs. The investments related to process technologies are very low for industrial businesses [143]. Since that, many businesses already deploy of metering and communication frames and structures, control and software technologies.

<u>Fixed Costs</u>: Fixed costs are subdivided into information, contract fee and control costs [144]. Compiling information for implementing decisions lead to Information costs. Transaction costs or contract fee costs are imposed through communication and control costs occurring through the planning and regulating of processes containing DR.

These three kinds of fixed costs so significantly cause costs as personnel. Moreover, data exchange between the business and a DR provider may cause the fixed costs [143]. Classification of DR costs and benefits for system operators or other DR program operators is demonstrated in Figure 3.6 at one look.

<u>Variable Costs</u>: The U.S. Department of Energy explains the variable costs in terms of opportunity costs. It can be considered that variable costs to a large degree arise from process technologies because short-term technologies do not naturally make an impact on the products of the business.

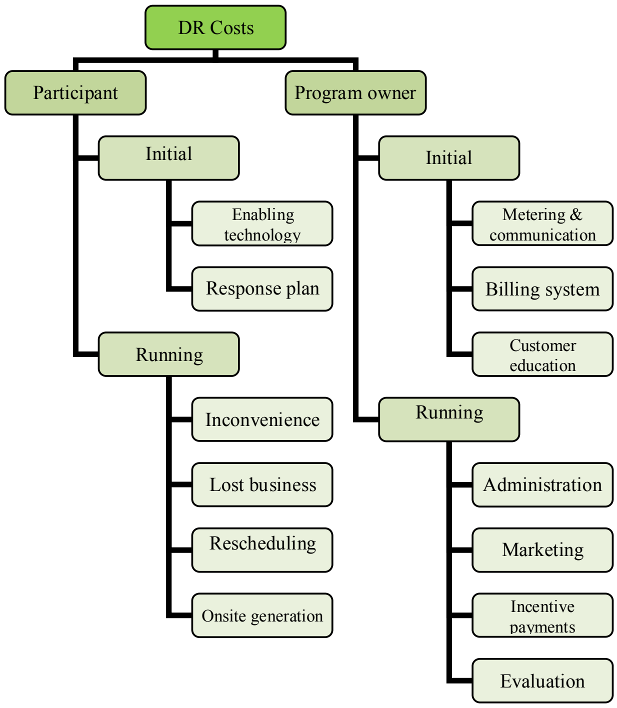


Figure 3.4- Classification of DR costs [17].

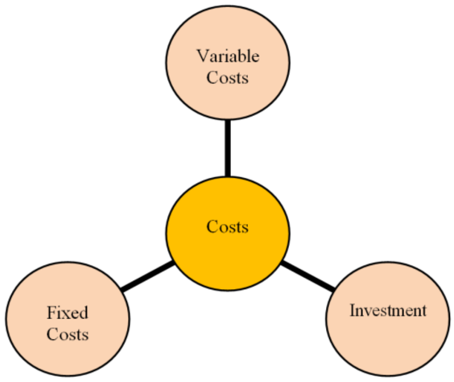


Figure 3.5- Classification Costs for system operators or other DR program operators are subdivided into three major categories [140].

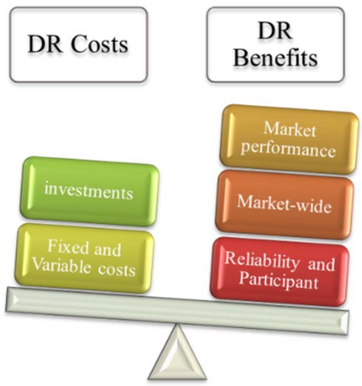


Figure 3.6- Classification DR costs and benefits for system operators or other DR program operators at one look.

In this chapter, DR and renewable energies comprehensive review the latest modifications in DR definition and classifications were scrutinized. Moreover, benefits and related expenditures were categorized extensively. DRPs make a tremendous impact on the market prices and bring them down, enhance system reliability, improve the flexibility of the system and reduce changing frequently of electricity prices.

To employ DRPs, both customers and program operators associated with a variety of costs. The amounts of decrease in peak load and demand elasticity are the items to measure the performance beneficial of DRPs. Although latest researches and source scheduling studies illustrate more considerable profits from DR programs, program assessment studies go to prove the significant benefits of these practical programs.

A literature review of the very recently published papers about DRPs associated with renewable energies was presented. Eventually, using DR programs and renewable resources in the smart grids and power system points of view or in various electrical power markets was investigated. A comprehensive classification of recent researches methods for optimization in the intraday market, day-ahead market, balancing market and DRX market was proposed.

3.6 Stochastic Programming and Uncertainty Characterization via Scenarios

Unknown data abound in decision-making problems in the real world. This lack of perfect information is common in problems belonging to different knowledge areas such as engineering, economics, finances, among others.

Decision-making problems in electricity markets are no exception. In fact, uncertainty is present in most decision-making problems faced by electricity market agents. For example, electricity prices are unknown when agents have to submit their offers or bids to the pool. Similarly, at the time of procuring the energy needed to supply client loads, retailers do not know precisely the electricity demands of these clients.

However, decisions need to be made even with lack of perfect information. This is what motivates the use of stochastic programming models for decision making under uncertainty. Most decision-making problems can be adequately formulated as optimization problems. If the input data of an optimization problem are well-defined and deterministic, its optimal solution (decision) is achieved by solving the problem. The decision is then implemented to attain the best outcome.

However, more often than not, the input data are uncertain but describable through probability functions. In such a situation, it is not clear how the decision-making problem should be formulated. One possibility is to substitute the uncertain input data (describable through probability functions) by their corresponding expected values, which results in a well defined and deterministic optimization problem. However, solving such a problem may lead to a solution that once implemented does not result in the best outcome.

Alternatively, the probability distribution of input data can be approximated by a collection of plausible sets of input data with associated probabilities of occurrence. For instance, three sets of input data with three values of probability of occurrence adding to 1.

Then, a stochastic optimization problem can be formulated implicitly weighting (with the probabilities of occurrence) the individual solutions associated with each set of input data to achieve a single solution that is the best in some sense for all sets of input data. That is, it achieves a solution that is adequately pre-positioned with respect to all the sets of input data, but not to any one of them particularly.

As a result of the uncertain input data being described by a collection of different sets of data, the resulting objective function is uncertain and needs to be characterized as a random variable. Since such objective function is not a real-valued function but a random variable, the problem of establishing a specific objective for the decision-making problem arises. One alternative is to maximize the expected value of the objective function, other one, to maximize the expected value of such function but limiting its variance, among others.

Implementing the solution obtained by solving the stochastic problem above pre-positions the decision-maker in the best possible manner if considering all possible input data sets duly weighted by their respective probabilities. This solution is not the best for each individual set of input data but it is the best if all of them, weighted with their probabilities of occurrence, are simultaneously considered.

The price to be paid for using a stochastic programming approach is a dramatic increase in the size of the problem to be solved, which if handled without care may lead to intractability. A wealth of motivating and clarifying examples can be found in tutorial reference [145]. This chapter describes the basics of stochastic programming. Additional information can be found in [146] and friendly tutorials are available in [147].

Many engineering and science problems are subject to uncertainty due to the inherent randomness of natural phenomena and/or to the imperfect knowledge of the variables determining the functional state of the human-created structures. In this context, computational methods that tackle uncertainty allow engineers and scientists to propose solutions less sensitive to environmental influences, while achieving simultaneously cost reduction, profit gains, and/or reliability improvement.

Decision-making problems related to electricity markets are not exempt from uncertainty. The own rules governing the functioning of these markets can be deemed responsible for the existence of uncertainties conditioning market agents' behavior. For instance, energy prices are known after producers and consumers submit their selling offers and purchasing bids, respectively, to the electricity market. As a result, decisions on the amount and price of the energy to be sold or purchased are irremediably made with inaccurate knowledge of the final market outcome.

Likewise, the time-gap existing between agreements on energy transactions and their physical implementation causes that a producer must face the trading process with a certain degree of uncertainty about the availability of its power sources. This chapter is specifically intended to provide general guidelines on how to build appropriate scenario sets representing the typical stochastic processes involved in electricity market problems.

3.7 Scenario Generation

3.7.1 Overview

In decision making under uncertainty, the decision maker has to make optimal decisions throughout a decision horizon with incomplete information. Over the considered decision horizon, a number of stages are defined. Each stage represents a point in time where decisions are made or where uncertainty partially or totally vanishes. The amount of information available to the decision maker is usually different from stage to stage.

According to the number of stages considered we can distinguish between two-stage and multistage stochastic programming problems. In this decision-making process, two different kinds of decisions are distinguished:

- First-stage or here-and-now decisions. These decisions are made before the realization of the stochastic process. Hence, variables representing here-and-now decisions do not depend on each realization of the stochastic process;
- Second-stage or wait-and-see decisions. These decisions are made after knowing the actual realization of the stochastic process. Consequently, these decisions depend on each realization vector of the stochastic process.

If the stochastic process is represented by a set of scenarios, a second stage decision variable is defined for each single scenario considered. The decision framework above is conveniently visualized through a scenario tree, as the one in Figure 3.7. Graphically, a scenario tree comprises a set of nodes and branches. The nodes represent states of the problem at a particular instant, i.e., the points where decisions are made.

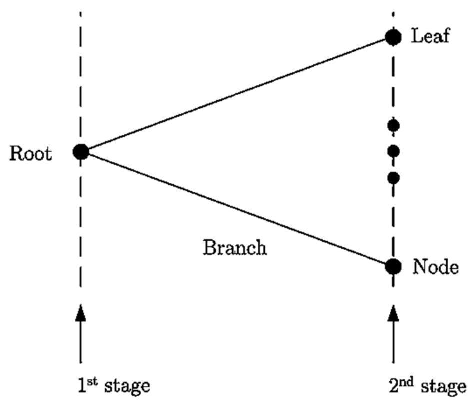


Figure 3.7-Scenario tree for a two-stage problem [148].

Each node has a single predecessor and can have several successors. The first node is called the root node, and it corresponds to the beginning of the planning horizon. In the root node, first-stage decisions are made. The nodes connected to the root node are the second-stage nodes and represent the points where the second-stage decisions are made.

For a two-stage problem, the second-stage nodes are equal to the number of scenarios and are referred to as leaves. In a scenario tree, the branches represent different realizations of the random variables. Note that for all these decisions to be optimal, they need to be derived simultaneously by solving a single optimization problem, so that the relationships among the decision variables are properly accounted for.

It is important to note that stochastic programming problems can be mathematically formulated using either a node-variable formulation or a scenario variable formulation. The first formulation relies on variables associated with decision points while the second one relies on variables associated with scenarios.

The first formulation is comparatively more compact than the second one and is particularly well suited for a direct solution approach; the second one requires a larger number of variables and constraints than the first one but presents an exploitable structure that is well suited for decomposition.

In some cases, decision-making problems comprise more than two stages. This fact motivates the use of multi-stage stochastic programming problems. This decision framework is conveniently visualized through a scenario tree, as the one in Figure 3.8. Graphically, a scenario tree is depicted as a set of nodes and branches.

The nodes represent states of the problem at a particular instant, i.e., the points where decisions are made. In the first node, called the root, the first-stage decisions are made. The nodes connected to the root node are the second-stage nodes and represent the points where the second-stage decisions are made. The number of nodes in the last stage equals the number of scenarios. These nodes are referred to as leaves. In a scenario tree, the branches are different realizations of the random variables.

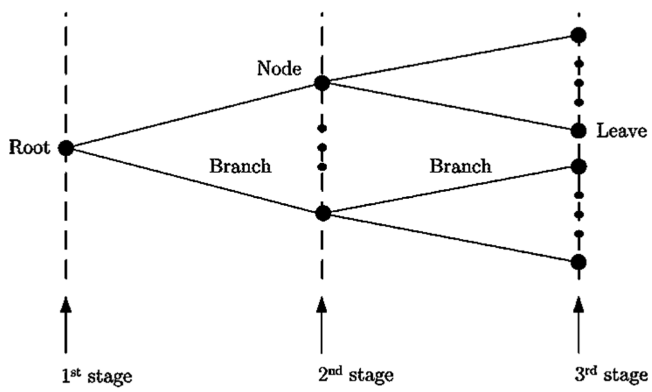


Figure 3.8- Scenario tree for a three-stage problem [148].

Since the size of a stochastic programming problem, measured in terms of its number of variables and constraints, grows with the number of scenarios, stochastic programming problems become easily large-scale involving millions of variables and constraints. It is thus important to select carefully the number of scenarios to properly represent the stochastic processes involved.

However, stochastic programming problems present often an exploitable structure. Typically, the number of constraints involving variables across scenarios is comparatively small with respect to the number of variables and constraints pertaining to any particular scenario. These linking constraints are mostly non-anticipatively conditions. Note that this structure is particularly exploitable if a scenario-variable formulation is used.

Thus, stochastic programming problems generally include complicating constraints, i.e., constraints that if relaxed render the resulting problem easy to solve as it decomposes by scenario. Therefore, decomposition techniques are particularly suited to tackle stochastic programming problems. A description of decomposition procedures for mathematical programming problems can be found in [149]. Some general rules on which solution technique to be used follow:

- If the problem under consideration is linear and involves no discrete variables, its solution can be addressed directly for sizes up to a few million variables/constraints;
- If the problem is linear but involves discrete variables, depending on the number of discrete variables and the structure of the problem, either a direct solution technique or a decomposition procedure would be advisable;
- Similarly, if the problem is nonlinear and continuous, depending on the number of variables and the structure of the problem, either a direct solution technique or a decomposition procedure would be advisable;
- Finally, if the problem is nonlinear and involves continuous as well as discrete variables, a decomposition procedure is generally advisable.

As a consequence of the broad and versatile capabilities of currently available optimization solvers [150], throughout this thesis, the only solution technique actually considered is direct solution. For this reason, all models formulated are linear, mixed-integer linear or mixed-integer quadratic. Other solution approaches are outside the scope of this thesis. Nevertheless, a variety of effective solution techniques based on decomposition are reported in the technical literature [149].

In stochastic programming, stochastic processes can be represented using continuous or discrete random variables. In the best case, stochastic programming problems with continuous random variables can only be solved in small or illustrative instances. In point of fact, evaluating a possible solution in this kind of problems is frequently impossible. For this reason, the discrete representation of random variables using a finite set of possible outcomes becomes indispensable in actual decision-making problems under uncertainty.

Nevertheless, the appropriate representation of a continuous random variable using a finite set of values can be more difficult and time consuming than formulating and solving the resulting stochastic programming problem.

For this reason, significant effort has been paid by the research community on this issue. The set of finite values used to model a random variable is usually arranged in a so-called scenario tree. Graphically, a scenario tree comprises a set of nodes and arcs. The nodes represent states of the "world" at a particular instant, and those nodes constitute the points where decisions are made.

Each node has a single predecessor and can have several successors. The first node is called the root node, and it corresponds to the beginning of the planning horizon. In the root node the first-stage decisions are made. The nodes connected to the root node are the second-stage nodes and represent the points where the second-stage decisions are made. The nodes in the last stage are referred to as leaves. Each single path between the root node and a leave is named scenario.

In a scenario tree, the arcs represent different realizations of the random variables. Each arc has associated a probability of occurrence. In this way, the probability of a scenario is the product of all arc's probabilities associated with that scenario. Different techniques have been proposed in the technical literature to build scenario trees. Some relevant methods are the following:

- Generation of data trajectories or path-based methods: These methods generate complete paths or scenarios by means of econometric and time series models. The set of scenarios obtained by these methods is called a fan. Once the fan is generated, the scenarios are clustered to build the scenario tree. A relevant reference using path-based methods is [151];
- Moment matching: These methods generate discrete distributions that satisfy a prefixed set of statistical properties (e.g., based on moments, correlation matrix, percentiles, etc.) characterizing the original distributions of the random variables. Relevant references on moment matching are [152], [153];
- Internal sampling: The internal sampling consists in a continuous sampling process from the original distribution functions of the random variables during the solution procedure. References on internal sampling methods are [154], [154];
- Scenario reduction: These methods begin from a large set of randomly generated scenarios. This original set is reduced to a new set of prescribed cardinality, whose final distribution function is close enough to the original one according to a given probability metric. References using scenario-reduction methods include [155], [156].

3.7.2 Quality of Scenario Subsets

Stochastic processes are represented in stochastic programming problems using a finite set of possible realizations arranged in a so-called scenario tree. It should be clear that scenario trees are needed because realistic stochastic programming problems including continuous expressions of the stochastic processes are usually impossible to solve.

In fact, only illustrative instances or small examples can be solved directly. For this reason, how to build appropriate scenario trees has become an active research field for stochastic programming theorists and practitioners during the last decades.

The question that arises here is what is an appropriate scenario tree? In theory, the answer is easy: a good scenario tree is that which included in the stochastic programming problem results in the same solution than that obtained by using the continuous representation of the stochastic processes. However, verifying this condition is not trivial since, as we mentioned above, stochastic programming problems with continuous stochastic processes cannot be solved in general.

Significant effort has been made in order to measure the error associated with the usage of a discrete representation of the stochastic process instead of the continuous one. This error is usually expressed in terms of the difference between the objective functions of the discrete and continuous stochastic problems.

Note that this error could be also expressed in terms of the resulting optimal decisions. Notwithstanding this, measuring the error by using objective function values is preferred because objective functions of stochastic programming problems are usually flat and different decisions may yield similar objective functions.

In [157] an upper bound of the error of using discrete representations for the stochastic processes is derived. This upper bound is obtained under some mild Lipschitz conditions of the objective function of the underlying problem. Additionally, in [158] some hints are given on which properties good scenario trees should meet.

The first requirement is the stability of the scenario trees. In other words, several trees randomly obtained using the same scenario generation procedure should provide (almost) the same solution to the stochastic problem considered. This property can be easily tested by generating several scenario sets and studying the optimal solutions achieved. If these solutions are (almost) the same, it can be said that there exists in-sample stability.

If, in addition, it is evaluated the true objective function for the set of optimal decisions that results from each scenario tree and we obtain (almost) the same values, then, the results are in an out-of-sample stability case. Clearly, since in this case it is necessary to compute the true objective function, testing out-of-sample stability is more complicated than testing in-sample stability.

The second requirement is that the solution obtained with the scenario tree should be unbiased with respect to the true solution obtained with the continuous process. This requirement is difficult to check because, as we already know, the true solution is unknown. For this reason, an approximate method consists in building a reference tree representing the continuous (or true) process as well as possible.

One important issue is that this reference tree must ensure unbiased solutions. The optimal decisions obtained from the trial tree can be tested on the reference tree and the resulting value of the objective function can be compared with that obtained from solving the problem with the reference tree directly. The reference tree should be as large as possible and it should not be generated using the same procedure than that used for generating the trial tree.

Another relevant issue for discussion is the shape of the scenario tree. That is, it must be determined how many stages the tree comprises and how many branches leave each node. Observe that the number of stages results directly from the considered decision-making problem, whereas the number of branches leaving each node is a decision that the modeler has to make. However, if a scenario-reduction procedure is used, the final number of branches leaving each node results automatically from using this procedure.

3.8 Scenario Reduction: The Motivation

The scenario-generation technique described in the previous Subsections is based on a sampling approach. That is, after identifying the time series model that best represents the continuous stochastic process under study, a repeated random generation of white noises is performed to produce a discrete approximation in the form of a scenario set. Consequently, in order for this approximation to be accurate, a high number of scenarios are usually required.

Given that the computational burden of a stochastic programming model rapidly increases with the number of scenarios, a mathematical tool aimed to shrewdly reduce such a number becomes a need. In other words, the necessity of reconciling scenario generation and computational tractability is what justifies the existence of scenario-reduction techniques.

In more detail, a scenario-reduction methodology seeks to downsize a scenario set while still keeping as intact as possible the stochastic information embedded in it. Logically, the quality of the reduction process is measured in terms of the solution to the underlying optimization problem. In this line, a good reduction process results in a reduced scenario set that yields an optimal solution close in value to the solution obtained from the initial one.

Finally, the original structure of the tree must be preserved after applying the scenario-reduction technique. Since two-stage trees can be viewed as a fan of scenarios in which each branch belongs to a single scenario, the former consideration only affects to multi-stage trees. Note that in multi-stage trees some branches belong simultaneously to several scenarios.

In order to preserve the structure of the original tree in a multi-stage stochastic problem, caution should be exercised in the formulation of the non-anticipatively constraints presented in [67]. As stated in that reference, those constraints contain the information of the structure of the tree, and therefore they must be updated to take into account the elimination of some scenarios in the scenario-reduction process.

3.9 Final Considerations

This chapter provides an overview of stochastic programming. First, random variables and stochastic processes are introduced and their differences clarified. Scenario generation and reduction are then briefly considered. Emphasis is given to the commonly used two-stage problems.

Stochastic programming constitutes a powerful modeling framework to solve decision-making problems affected by uncertain input data. Previous to undertaking the solution of a stochastic programming problem, uncertainties on the problem parameters are to be modeled as stochastic processes.

In most cases, such a modeling endeavor includes the generation of a set of scenarios representing plausible realizations of the stochastic processes throughout the decision-making horizon. The number of scenarios needed to properly represent stochastic processes in electricity-market problems is generally very large, which may render the associated optimization problem computationally intractable.

For this reason, and as a complement to the scenario-generation topic, this chapter describes two efficient scenario-reduction procedures to trim down significantly the number of scenarios maintaining, as much as possible, the statistical information embedded in them.

In some electricity-market problems, the stochastic processes involved may be statistically dependent, and this dependency may have a non-negligible impact on the decisions to be made. This is particularly true, for example, in the case of producers with a generation portfolio including wind farms at several locations.

Therefore, in such instances, the scenario-generation methodology to be employed should be able to recognize and incorporate dependencies among stochastic processes, and produce scenarios in consequence. In short, it is possible to observe that:

- Stochastic programming constitutes a useful tool to make decisions under uncertainty;
- The two-stage stochastic programming models are particularly relevant for their practical interest, relative simplicity, and high versatility;
- Uncertainty is properly described through stochastic processes, which in turn are conveniently characterized using scenarios;
- A large enough number of scenarios need to be generated to accurately represent a stochastic process;
- More often than not the number of scenarios adequately describing a stochastic process is large, and thus the associated stochastic programming problem becomes computationally intractable;
- Therefore, scenario-reduction techniques are needed to attain tractability while keeping as much as possible the stochastic information embedded in the original scenario set;
- Uncertainties in optimization problems need to be often represented via scenarios;

- Tools for the analysis and modeling of time series can be exploited to design user-friendly scenario-generation techniques;
- For the sake of computational tractability, procedures intended to reduce the number of scenarios required to conveniently represent stochastic processes become a need in large-scale decision-making problems;
- Generally, those scenario-reduction techniques that use information of the optimization problem to be solved allow achieving a higher level of reduction for the same degree of accuracy;
- Dependencies among stochastic processes may have a significant influence on decision making, and therefore, such dependencies must be accounted for in the corresponding scenario-generation process;

Chapter 4

4. Market Clearing under Uncertainty: Wind Energy

4.1 Introduction

Power systems are subject to a great variety of uncertainties. Restructuring and competition in electricity systems are definitely contingent on the available means to overcome the difficulties brought by these uncertainties. In the case of electricity trade, holding a competitive framework constitutes a task tougher than for other commodities due to the particularities of the electricity transactions.

As a key example, the transmission of electrical energy is such that the production and consumption at a given bus of the system affect the entire system. Therefore, the actions to be carried out in order to accommodate these uncertainties without compromising the consistency of the trade call for a global management able to involve, if required, the participation of every agent in the system.

In [148], the reserve was introduced as the instrument to face power system uncertainties, and thus, to support energy transactions in electricity markets while guaranteeing a secure use of the electrical infrastructure. In pursuit of a comprehensive restructuring, the reserve, like energy, is managed, scheduled and traded through electricity markets. In that reference, the authors concluded that market-clearing procedures with stochastic security are appropriate tools to solve the tradeoff between economic efficiency and system security.

In practice, reserve scheduling translates into pre-positioning generating units and loads in the best possible manner to respond effectively to the realization of uncertainties in accordance with the available resources and their cost. The response usually consists in altering the production and consumption levels of generators and loads.

The magnitude and characteristics of the uncertainties present in power systems are crucial to the planning of the reserve. One of the main features of uncertainties related to equipment failures is its discrete nature, i.e., there exist a finite number of plausible realizations of the uncertain variables leading to a finite number of system states.

In this chapter, the market-clearing methodology is explained in order to account for the uncertainty associated with the continuous stochastic phenomenon representing the wind power production. Relevant references that highlight and address the new challenges arising from the large-scale penetration of wind generation into power systems include [156]–[164].

4.2 Wind Power Production

4.2.1 A Look to the Wind Generation

The issue of climate change has sparked discussion on the benefits of limiting industrial emissions of greenhouse gases in comparison with the costs that such alterations would entail. Reaching an agreement on this controversial subject seems to be difficult due to the time scales and uncertainties involved.

For the time being, climate change can only be strictly appraised in terms of the projected impacts for the coming decades, centuries, or even millennia of increasing temperatures, rising sea levels, heat waves, droughts, reduced crop yields and species extinction. However, beyond this controversy, one thing seems clear: if we desire to avoid the worst and irreversible damages of a plausible climate change, then global greenhouse gas emissions must begin to decline in the near future.

Governments in industrialized nations are currently subject to public opinion demanding actions to head of the worst impacts of climate change. These actions require addressing fundamental, long term structural adjustments to the global economy. A significant part of these structural changes is to be carried out in the electricity generation sector, where curbing emissions of greenhouse gases causing global warming is nowadays one of the most pressing issues.

In this sector, the measures undertaken to meet emission reduction targets have basically consisted in increasing the level of penetration of renewable and low carbon electricity generation resources, with wind power generation being the resource par excellence. In fact, at this time, wind energy is the only power generation technology that can enable the cuts in CO_2 emissions from the power sector necessary for fulfilling thee mission reduction targets agreed in some industrialized countries [161], [164].

Wind generation is free of emissions and promotes sustainable development. The energy source, the force of the wind, is indigenous and, as such, geopolitically generous, encouraging the self-sufficiency in energy of nations. Moreover, it uses no water. Technically, wind power is fast to deploy, economic and competitive, and generates employment.

As wind farms do not consume fuel, they can reduce fuel costs and offer a hedge against fuel price volatility. Wind power plants have low forced outage rates and can contribute to lessen the need for polluting generation sources.

4.2.2 Wind Impact on System Security

Wind power cannot be dispatched in a traditional sense due to the inherent randomness of the natural phenomenon involved: the wind. Therefore, wind generation is variable and uncertain, and consequently, its large-scale integration into a power system constitutes a unique challenge for system operators and planners [9], [159].

Actually, the management of uncertainties in a power system is not new for practitioners. The energy demand is also variable and uncertain, just like wind generation, and system agents have been coping with the natural variability and randomness of demand since the dawn of the power industry.

The integration of wind generation into a power system entails the consideration of additional amounts of uncertainty and variability in the operation of the system. This basic fact may be of the utmost importance taking into account the exigent wind penetration marks that several countries have set out to achieve. Part of this variability can be predicted some hours or days ahead.

The uncertain part of the variability is managed with reserves in the power system. As the level of wind power generation increases, the need for spinning and non-spinning reserves increases to maintain system security and this increase translates into higher reserve costs. In either case, the variability of wind power production, uncertain or predictable, requires operating the power system with a higher degree of flexibility in order to coordinate the following of the fluctuating load and the variable output of wind generation.

This greater flexibility usually leads to operate conventional generation at lower/higher production levels in an attempt to accommodate the inherent variability of wind generation by ramping up or down. These ramping excursions may often end up with the start-up or shut-down of conventional units.

On the other hand, the variability of power output has an impact on the capacity credit of wind generation. Capacity credits for wind plants do not approach nameplate ratings due to the non-controllability of the underlying energy source. In plain words, this means that in practice 1 MW of installed wind capacity is not adequate to cover 1 MW of demand in a reliable and secure manner. For all these reasons, new system operation planning methods are required to deal with the intricate nature of wind generation while preserving or even enhancing the current reliability and economic performance of power systems.

4.2.3 Accommodating Wind Uncertainty in Electricity Markets

The economic performance of power systems is contingent on the correct functioning of the electricity markets. According to the most basic economic principles, electricity markets driven by the invisible hand of competition should guarantee the economically efficient operation of electrical systems. However, when wind power comes on stage in high levels, the competitive functioning can be altered as the energy transactions settled in these markets may not be implemented in real-time, exactly as agreed, for security reasons.

Therefore, the proper integration of wind generation into power systems calls for markets decisions relying on economic criteria while maintaining or even improving the reliability of the electrical infrastructure and its operation. The reliability and security of power systems is largely dependent on the reserve management, which, in turn, is conditional on the amount of wind power planned [159]. In this respect, there are several issues related to reserves that need to be assessed:

- Scheduling and allocation of reserves: how much capacity has to be allocated for each day. The system operator must ensure that an adequate amount of reserve is kept in power plants in order to face the unpredictable variability of wind generation;
- Deployment or use of reserves: how the scheduled reserves are utilized in real time as the wind uncertainty is revealed.

The market-clearing model is formulated as a two-stage stochastic programming problem, where the first and second stages represent, respectively, the electricity market and the real-time operation of the power system. In consequence, the variables belonging to the first stage are the market decisions that envisage the impact of the plausible realizations of wind power uncertainty on system variables, i.e., on second-stage variables.

Hopefully, the steady progress in computing technologies could well overcome those difficulties in the future. However, in the meantime, the market-clearing models presented can be used by the system operator as a tool to evaluate the reserve needs from a market viewpoint in the short, mid and long term [166]. This analysis would be based on historical records and forecasts of market agents' behavior and wind power production.

4.3 Market-Clearing Model

In order to cope with the uncertainty of wind generation, some adjustments are to be implemented within the market-clearing model. In spite of the necessary revision to be performed, the main features characterizing the previous market-clearing procedure remain intact.

Thus, the management of the stochastic nature of wind power generation is accomplished through a two stage stochastic programming problem where the first stage models the functioning of the electricity market and the second one, the real-time operation of the power system.

Mathematically, it is build an optimization problem in which the objective function, representing the expected social cost, is subject to three sets of constraints: the first one modeling the energy and reserve transactions in the electricity market; the second one modeling the actual operation of the power system once the wind power production is certainly known; and lastly, the linking constraints that couple market decisions with real-time operating actions executed via the deployment of reserves.

From a mathematical programming viewpoint, the optimization model is formulated as a large-scale mixed-integer linear problem [168] that can be solved using commercially available software [150].

4.3.1 Assumptions

Apart from the considerations concerning the linear approximation of the network and the cost of the reserve deployment, the market-clearing formulation designed to handle wind uncertainty is based on the following additional assumptions:

- Without loss of generality, equipment failures are not considered. This assumption allows us to underline the differences between the treatment of wind uncertainty and equipment contingencies;
- For the sake of simplicity, wind generation is located at a single node of the power network. If wind power is produced and then injected at different nodes within the grid, the rigorous management of wind uncertainty calls for the statistical analysis and modeling of the likely spatial interrelations among wind sites;
- Wind generation is assumed to be a regulated activity and thus wind producers do not compete in the market. Consequently, wind generation is either considered a negative demand or spilled, and thus, paid a regulated tariff. Note that this is the case in which wind power is treated in most energy systems throughout the world. Additionally, observe that this assumption is equivalent to considering that wind generators offer in the pool their actual productions at zero prices.

It should be stressed that these three assumptions are made just in order to free the proposed market-clearing procedure of complexities that can complicate its understanding unnecessarily. The treatment of the uncertainty associated with wind power in a stochastic programming framework should generally comprise two phases.

The first one consists in the accurate modeling of the wind power stochastic behavior by generating a sufficient number of scenarios representing the most plausible realizations of wind power throughout the scheduling horizon. The second phase is required because the size of this initial scenario set is usually too large, resulting in an optimization model that is intractable. Hence, to achieve tractability, statistical techniques [155], [156], [169], [170] are applied to reduce the number of scenarios while retaining the essential features of the original scenario set.

Finally, the set of scenarios together with the decision timing of the problem can be arranged in a two-stage scenario tree as illustrated in Figure 4.1. The first stage (root node) represents the electricity market, where decisions pertaining to the scheduling of energy and reserve are made. The second stage (leaf nodes) constitutes the real-time operation of the power system which revolves around the deployment of reserves in order to accommodate the specific realization (scenario) of the wind power production.

From an intuitive point of view, the aim of any stochastic programming model in the market clearing procedure is to locate the root node at a stochastically equidistant position with respect to the leaf nodes.

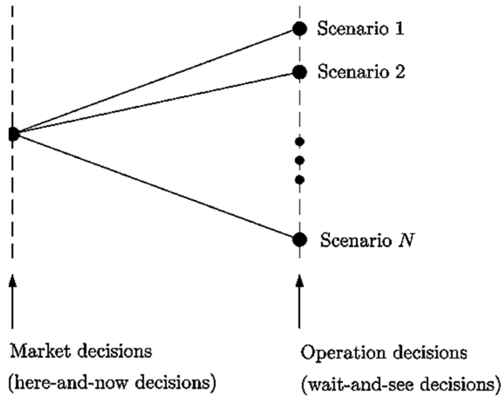


Figure 4.1- Scenario tree example for the market-clearing problem with wind generation [148].

All generated scenarios in this thesis, were decreased to 10 more probable scenarios due to reduce the computational complexity. The reduction methods alleviate the complexity making the models easier to manage. The wind speed scenarios are generated based on South East and North of South Australia wind speed data by means of an Autoregressive Moving Average (ARMA) model [46].

In order to have a tractable optimization problem without extra computational difficulties, the generated scenarios are reduced to ten scenarios for each wind farm using K-means clustering technique [171].

The employed scenarios are depicted in Figure 4.2. Afterward, the remaining wind speed scenarios are transformed into wind power scenarios according to the Vestas 3 MW turbine features.

4.3.2 Stochastic Network-Constrained Market Clearing Formulation

In order to simulate the two-stage operation of day-ahead and real-time electricity markets in the presence of volatile wind generation, a two stage stochastic market clearing model is conducted. The applied two-stage stochastic programming is well-known and has been used in same problems, already [172].

The first-stage decision variables are market-based variables; those are not dependent on scenarios occurrence including start-up and shut-down plan of each generation unit, scheduled power of generation units in energy and up/down capacity reserve markets.

The second-stage decision variables are real-time scenario dependent variables that should be altogether considered (according to their probability) in order to obtain a single day-ahead market clearing.

The second-stage decision variables are the up/down deployed reserve by each generation unit, the involuntary load shedding by each load, and wind power spillage of each wind farm. The proposed model aims to determine an optimal wind-thermal generation scheduling considering versatile DR programs with application to facilitate wind power integration.

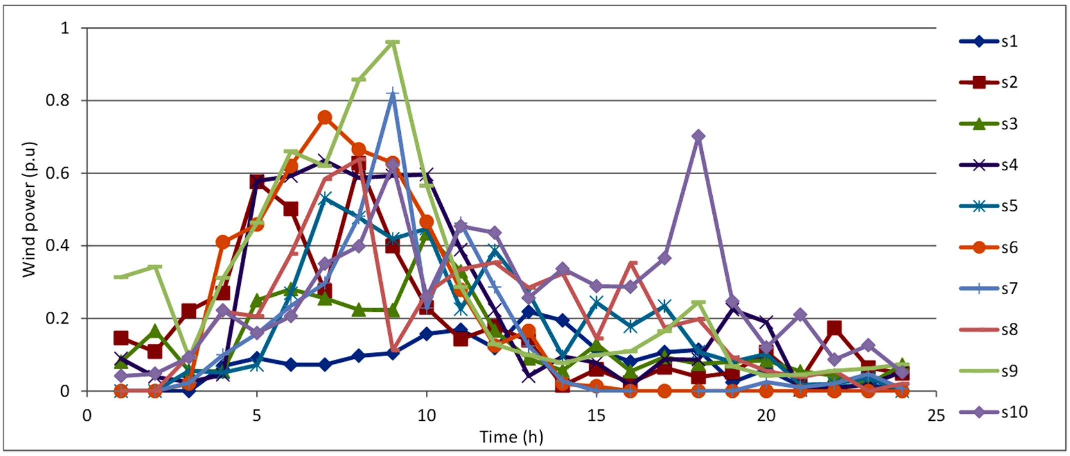


Figure 4.2- Considered wind power generation scenarios.

The objective function is the expected system operation cost which should be minimized while meeting several constraints from the ISO's viewpoint as given in Equation 4.1:

$$
\begin{aligned}
&OPC = \\
&\sum_{t=1}^{NT}\Bigg[\sum_{i=1}^{NG}(SUC_{i,t} + MPC_i U_{i,t} + \sum_{i=1}^{NG}\sum_{m=1}^{NM} P^{e}_{i,t,m}\, C^{G\_Eng}_{i,t,m} \\
&+ C^{G\_UC}_{i,t} R^{G\_UC}_{i,t} + C^{G\_DC}_{i,t} R^{G\_DC}_{i,t}) \\
&+ \sum_{j=1}^{NJ}\left(Inc_t \Delta d_{j,t} - Pen_t\left(d^{contract}_{j,t} - \Delta d_{j,t}\right)\right)\Bigg] \qquad (4.1) \\
&\qquad + \sum_{t=1}^{NT}\sum_{w=1}^{NW}\rho_w\left(\sum_{i=1}^{NG} C^{G\_UE}_{i,t} r^{G\_up}_{i,t,w} - C^{G\_DE}_{i,t} r^{G\_dn}_{i,t,w}\right. \\
&\qquad \left. + \sum_{j=1}^{NJ} Voll_{j,t} LS_{j,w,t} + \sum_{wf=1}^{NWF} C^{WP\_spill}_{wf} P^{WP\_spill}_{wf,w,t}\right)
\end{aligned}
$$

The first and second line terms in Equation 4.1 subsequently indicate the operation cost resulted from start-up, minimum production, piecewise linear fuel and up/down capacity reserve cost of generation units. The first term of the third line of Equation 4.1 denotes the cost of incentive payment to customers who successfully response to IBDRPs.

Moreover, the second term is the income of penalty received from customers who avoid reducing their demand according to the contract. The other part of costs in Equation 4.1 is devoted to the corrective action costs as a result of wind power scenario realization during the real-time stage.

The cost terms regarding up/down deployed reserve of generation units, involuntary load shedding and wind spillage are formulated in the two last lines of Equation 4.1, respectively. Note that, the considered day-ahead DR model is completely certain without any uncertainty in customer's response. On this basis, there is no variability in the amount of demand and hence, just the wind power variability should be justified in real-time electricity market. The objective function must be minimized subject to several constraints related to generation units, network and wind power generation, as declared in the following.

The load-generation balance is formulated in Equation 4.2. Note that, $d_{j,t}$ in Equation 4.2 is expressed the modified demand of load j, at hour t, after implementing DR, and then assigned to relevant buses. Also, $P_{i,t}$ denotes the aggregated power generation of generation unit i at hour t calculated from the sum of generating unit's piecewise offered energy blocks as expressed in Equation 4.3. The power flow is computed in Equation 4.4, while its bounds are enforced in Equation 4.5.

The negative sign in left hand side of Equation 4.5 is related to the direction of power flow. In fact, the power flow can be in both directions and the absolute value of power flow must be less than the maximum allowable amount in both directions.

$$\sum_{i\in G_b} P_{i,t} + \sum_{wf\in WF_b} P_{wf,t}^{WP,S} - \sum_{j\in J_b} d_{j,t} = \sum_{l\in L_b} F_{l,t}^{0} \tag{4.2}$$

$$P_{i,t} = \sum_{m=1}^{NM} P_{i,t,m}^{e}\ ,\ 0 \le P_{i,t,m}^{e} \le P_{i,m}^{\max} \tag{4.3}$$

$$F_{l,t}^{0} = \left(\delta_{b,t}^{0} - \delta_{b',t}^{0}\right)\Big/ X_l \tag{4.4}$$

$$-F_l^{\max} \le F_{l,t}^{0} \le F_l^{\max} \tag{4.5}$$

The generation unit constraints are listed in Equations 4.6–4.10. The minimum and maximum power output limits of generating units considering their scheduled power in both energy and reserve markets are set in Equation 4.6 and Equation 4.7. Up and down capacity reserves are bounded due to ramp rates as given in Equation 4.8 and Equation 4.9, respectively.

RU and RD in Equation 4.8 and Equation 4.9 are ramp-up and ramp-down characteristic of generation units, respectively. According to these two constraints, the assigned up/down reserve capacities must be less than the up/down ramp limits. The minimum up and down time constraints on conventional generators are enforced in Equation 4.10 and Equation 4.11. The start-up cost of generation units is formulated in Equation 4.12. The scheduled power of wind farms is bounded by 0 and its forecasted value in Equation 4.13.

$$P_{i,t} + R_{i,t}^{G\_UC} \le P_i^{\max} U_{i,t} \tag{4.6}$$

$$P_{i,t} - R_{i,t}^{G\_DC} \ge P_i^{\min} U_{i,t} \tag{4.7}$$

$$0 \le R_{i,t}^{G\_UC} \le RU_i \tag{4.8}$$

$$0 \le R_{i,t}^{G\_DC} \le RD_i \tag{4.9}$$

$$\sum_{t'=t+2}^{t+MUT_i} \left(1 - U_{i,t'}\right) + MUT_i \left(U_{i,t} - U_{i,t-1}\right) \le MUT_i \tag{4.10}$$

$$\sum_{t'=t+2}^{t+MDT_i} U_{i,t'} + MDT_i \left(U_{i,t-1} - U_{i,t}\right) \le MDT_i \tag{4.11}$$

$$SUC_{i,t} \ge SC_i (U_{i,t} - U_{i,t-1}) \tag{4.12}$$

$$0 \le P_{wf,t}^{WP,S} \le P_{wf,t}^{WP,\max} \tag{4.13}$$

There is another set of constraints that should be satisfied for each scenario realization. The nodal power balance is guaranteed in Equation 4.14 when each scenario occurs. The deployed up and down spinning reserves in each scenario must be less than the scheduled reserve capacities established by the market clearing as illustrated in Equation 4.15 and Equation 4.16, respectively.

The net output power of generation units is formulated through an auxiliary variable $P_{i,w,t}$, in Equation 4.17 and restricted by Equation 4.18. The $r_{i,w,t}^{G\_up}$, and $r_{i,w,t}^{G_dn}$can appear simultaneously in Equation 4.17. However, it is worth noting that one of the mentioned variables has zero value at each time slot and the other one is not zero.

This is due to the fact that just one of over or under estimation condition is happened in each time period. Ramp-up and ramp-down rate limits are subsequently considered in Equation 4.19 and Equation 4.20. Moreover, the bounds on wind power spillage and load shedding amounts are formulated in Equation 4.21 and 4.22, respectively.

$$\sum_{i\in G_b}\left(r_{i,w,t}^{G\_up}-r_{i,w,t}^{G\_dn}\right)+\sum_{wf\in WF_b}\left(P_{wf,w,t}^{W}-P_{wf,t}^{WP,S}-P_{wf,w,t}^{WP\_spill}\right)+\sum_{j\in J_b}LS_{j,w,t}=\sum_{l\in L_b}F_{l,w,t}-F_{l,t}^{0} \tag{4.14}$$

$$0\le r_{i,w,t}^{G\_up}\le R_{i,t}^{G\_UC} \tag{4.15}$$

$$0\le r_{i,w,t}^{G\_dn}\le R_{i,t}^{G\_DC} \tag{4.16}$$

$$P_{i,w,t}=P_{i,t}+r_{i,w,t}^{G\_up}-r_{i,w,t}^{G\_dn} \tag{4.17}$$

$$P_i^{\min}U_{i,t}\le P_{i,w,t}\le P_i^{\max}U_{i,t} \tag{4.18}$$

$$P_{i,w,t}-P_{i,w,t-1}\le RU_i\,U_{i,t}+SUR_i\left(1-U_{i,t-1}\right) \tag{4.19}$$

$$P_{i,w,t-1}-P_{i,w,t}\le RD_i\,U_{i,t-1}+SDR_i\left(1-U_{i,t}\right) \tag{4.20}$$

$$0\le P_{wf,w,t}^{WP\_spill}\le P_{wf,w,t}^{W} \tag{4.21}$$

$$0\le LS_{j,w,t}\le d_{j,t} \tag{4.22}$$

It is worth noting that the constraints such as DC power flow and thermal limits of transmission lines have been also considered for each occurred scenario even if their mathematical formulation is omitted for the sake of conciseness.

4.4 Wind Uncertainty vs. Equipment Failures

The occurrence of wind power spillage can be due to both economic and technical reasons. As we already know, the uncertain nature of wind generation requires scheduling reserves to guarantee and preserve system security.

This operation entails a cost. Consequently, if the benefit inherent to the cost-free character of wind energy is smaller than the cost associated with the management of its unpredictability, then wind spillage turns out to be profitable. Likewise, the variability of wind generation calls for a flexible operation of the power system.

Hence, the physical limitations of the electrical infrastructure impose a cap on the amount of wind power that can be injected into the network and the remaining wind power production has to be spilled as a consequence.

As a consequence, the real-time operation of the power system follows the scheduling program settled in the electricity market as long as no contingency takes place. The insertion of the non-anticipatively constraints (recall that the aim of these constraints is to guarantee that no corrective action is executed before the occurrence of a failure event) into the market-clearing model is closely linked to the discrete nature of equipment contingencies, which manifests itself as a system failure occurring at a certain instant, in time within the scheduling horizon.

Prior to that instant, there is no sign of the impending failure, there is no way to preempt it, and therefore, there is nothing to react against. In contrast, wind power constitutes a stochastic process whose uncertainty is revealed on a continuous basis, which compels the system operator to undertake corrective measures from the very beginning of the scheduling horizon. For this reason, such non-anticipatively constraints become inconsistent when dealing with wind uncertainty.

4.5 Performance Metrics

Uncertainties are the key elements that can affect the expected schedules and system regulation. To investigate the impacts of different DR programs on promoting grid integration of wind power, in this context are introduced some novel metrics and measures based on load changes.

The average Demand Response Program Benefit (DRPB) investigates the increase in social welfare as a result of the participation of 1 MW of load in the DR program. This index illustrates a more useful program to overcome the uncertainty of the wind. The index is represented by (23).

$$DRPB = \frac{1}{24}\sum_{t=1}^{24}\frac{SW_t^{NoDR} - SW_t^{DR}}{MAX^{DR} \times Load_t} \tag{4.23}$$

where MAX^{DR} is the percentage of consumers who are responsive demand and here it is assumed to be 20%.

Load modifications are very important for wind power activities; therefore, an index to investigate the effect of different DR programs on grid integration of wind power is introduced. This index, which is called demand response benefits for social welfare (DRSW), indicates the impact of DR on social welfare in the presence of wind power generation. In other words, it presents an increase in social welfare as a result of the integration of 1 MWh of extra wind power.

In fact, the $DRSW$ index shows the impact of DR implementation as a result of the injection of an extra 1 MWh of wind power in the power system on the average social welfare growth. This index is formulated by Equation 4.24.

$$DRSW = \frac{1}{24}\sum_{t=1}^{24}\frac{SW_t^{DR} - SW_t^{NoDR}}{\sum_{w}\rho_w . P_{wf,w,t}^{W}} \tag{4.24}$$

$DRSW$ is created to analyze the impact on the social welfare as a result of the penetration of wind units when implementing a variety range of DRPs when the amount of power generated by the system is increased by the injection of an additional 1 MWh of wind power. In the numerical result section, the effect of the different percentages of wind penetration associated with the wide range of variant DRPs is investigated.

The main purpose of this thesis is to investigate the impact of the variety of IBDR and PBDR programs in a market-based power system in detail through a stochastic Security Constrained Unit Commitment (SCUC), IEEE test systems will choose for the case study. Numerical results have been obtained to demonstrate the abilities of the presented model.

4.6 Results and Discussions

The IEEE 6-bus test system is used to analyze the proposed model and indices formulations [173]. All the case studies have been solved using CPLEX solver 12.5.0 under General Algebraic Modeling System (GAMS) software. It is notable that, as our model is a MILP optimization, the CPLEX is a good choice for solving the large-scale MILP problems.

In addition to different types of TOU programs, RTP, CPP, and EDRP are studied. These programs are illustrated in detail in Table 1 and Table 2. It is assumed that 20% of consumers are responsive demand. The RTP program prices are received according to the simulation of the energy market without considering the DRPs.

The average of market prices is defined as energy tariff in all hours for the base case. For TOU and CPP programs, the mentioned tariff is defined as the tariff in the off-peak period. According to the Table 1, TOU-1 and TOU-2 have three steps of tariffs, while TOU-3 has four steps. While an incentive fee equal to 30% of the tariff is defined in term of the amount of demand reduction, the tariffs of EDRP are the same as the base case prices. The self and cross elasticities are based on [14].

Figure 4.3 illustrates the tremendous influence of a variety of DRPs tariffs on the final demand load curve in the peak hours due to the implementation of these kinds of programs in the system. As shown in Figure 4.3, the application of different types of DRPs brings down the load curve of customers on the demand side. Moreover, it can be found that the CPP-1 has the most impact on the curve. TOU-1 and EDRP have the second and third largest impacts, respectively.

Table 4.1- Tariffs/incentives of considered DRPs ($/MWH).

Case	Valley: 01:00-08:00h	Off-peak: 09:00-11:00h 22:00-24:00h	Peak: 12:00-14:00h; 19:00-21:00h	Critical peak: 15:00-18:00h
Base case (fixed-rate)	63.20	63.20	63.20	63.20
TOU-1	31.60	63.20	94.80	94.80
TOU-2	15.80	63.20	126.40	126.40
TOU-3	31.60	63.20	94.80	189.60
CPP-1	63.20	63.20	126.40	126.40
CPP-2	63.20	63.20	189.56	189.56
EDRP	63.20	63.20	63.20	63.20: tariff 18.90: incentive

Table 4.2- Real time prices ($/MWH).

Hour	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Price ($)	54.7	52.8	51.2	50.1	50.2	51.7	54.4	57.7	60.7	63.0	65.2	66.7
Hour	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Price ($)	67.9	69.2	74.7	82.1	82.4	72.5	71.6	66.9	66.9	64.9	59.8	59.0

In the following, the variant DRPs have been compared by employing the proposed indices. Figure 4.4 illustrates the impact of the varied amount of wind production along with the implementation of various DRPs tariffs. As can be observed, the more substantial the percentage of wind power production, the higher the DRSW index for all kinds of DRPs, in general. With the same amount of wind power in the power system, the DRSW index indicates that EDRP has the most profound effect on the efficiency of the market. Implementing the EDRP program with the same rate of wind power can have more influence on reducing the system operation cost. Similarly, TOU1 is one of the most effective DRPs. Furthermore, CPP1 and TOU2 have approximately identical impacts on the social welfare of power systems associated with renewable units.

In Figure 4.5, the second type of CPP program has the highest DRPB. Hence the program has the most effect on increasing the social welfare with a constant rate of wind power generation. The TOU3 program is followed by TOU2, and then TOU1 to have the higher DRPB index. The DRPB index illustrates that the EDRP program has the least impact on driving down the market price or pushing up the social welfare with a constant rate of the wind power generation compared with other DRPs. The other DR resources can be considered in future works.

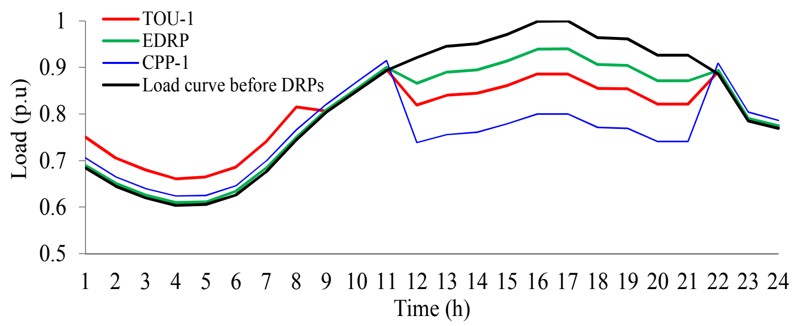


Figure 4.3- The impact of different types of DR programs after implementation on the final load curve.

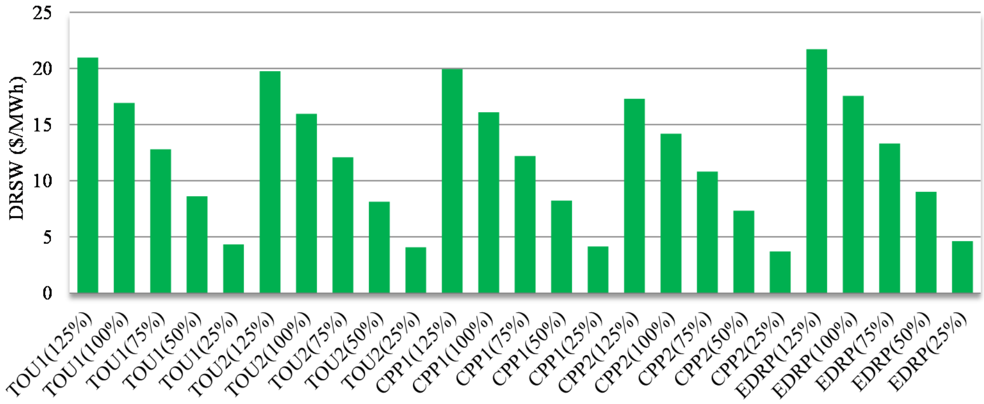


Figure 4.4- The impact of variant types of DR programs considering the different percentage of the wind penetration on the proposed DRSW index.

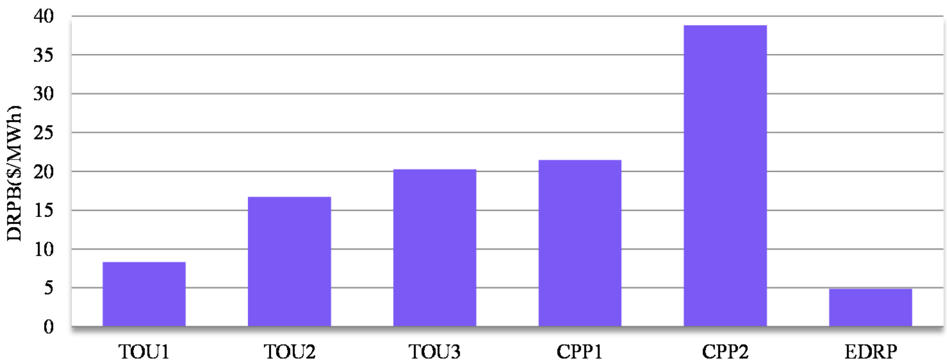


Figure 4.5- The impact of variant types of DR programs on the proposed DRPB index.

4.7 Final Considerations

The increase of wind power generation throughout the world has been remarkable in recent years, and its growth prospects in the decades to come are simply staggering. Wind is a form of renewable energy increasingly appealing from an economic viewpoint. It is gradually shaping up as a good bet for governments in industrialized and developing countries to curb emissions of greenhouse gases in response to public pressure on climate change.

However, wind power production is also uncertain and variable. As a result, it cannot be dispatched at the will of the producer. New methodologies are therefore required to incorporate wind generation into electricity markets enhancing their economic performance without making the power system any less reliable.

In this chapter, the market-clearing model with stochastic security briefly introduced to help meet that goal. The wind power production is treated as a continuous stochastic process, and as such, requires a discretization based on scenarios to be embedded into a stochastic programming optimization framework. The cardinality of the scenario set needs to be reduced using appropriate statistical tools with the aim of making the resulting mixed integer linear programming problem tractable.

Even after this reduction, the optimization problem is highly demanding computationally, and thereby, additional simplifications may have to be implemented to achieve the optimal or an approximate solution in reasonable time for realistic applications. Extensive simulations allow it to be concluded that:

- Wind generation decreases expected operation costs, but increases the costs pertaining to scheduling of reserves.
- The reserve cost due to wind power uncertainty is relevant in comparison to the costs related to energy production.
- Network congestion may seriously hinder the cost reduction achievable by wind generation.
- The consideration of a wind spillage cost may have a significant impact on scheduled reserves and on generation/demand scheduling.

Chapter 5

5. Prioritizing the Effectiveness of a Comprehensive Set of DRPs on Wind Power Integration

5.1 Introduction

The environmental targets set by power sectors throughout the world are the main drivers toward increasing the share of variable renewable energy sources (VRESs). Growth of VRESs will lead to a higher demand for operational flexibility due to their stochastic nature. Traditionally, conventional generation units provide the major share of additional required flexibility that may result in a higher depreciation.

Motivated by this challenge, this thesis investigates the potential of DR as an emerging alternative in systems with significant amounts of wind power. To this end, a comprehensive set of DR programs including tariff-based, incentive-based and combinational DR programs are considered in a stochastic network-constrained market clearing framework. Afterward, various DR programs are prioritized taking into account the system operator's economic, technical, and environmental desires.

Moreover, the sensitivity of different DR programs into customer's price elasticity of demand as well as participation level is evaluated by means of several sensitivity analyses. The obtained results can provide a guideline for the system operators to opt the most effective DR program.

It seems very crucial to investigate the impacts of implementing versatile DR programs on wind power integration in order to provide a guideline for ISOs to opt the most effective DR program. In this regard, there are relevant works that have already addressed the role of DR in mitigating the variability of wind generation across transmission grids.

Although DR programs implementation have been studied in the literature, there is no previously published paper so far which analyzed the impacts of a comprehensive set of DR programs including IBDRPs, TBRDRPs and combinational DR programs on wind power integration.

Moreover, most of the previous works investigated the role of DR programs from an economic viewpoint without paying attention to the technical and environmental aspects of DR on generation mixture.

From an economic point of view, the most effective DR program has a more reduction in system's operation cost while from a technical perspective, it must help to decrease the conventional fleet ramp need in the presence of stochastic wind generation. Environmentally, an efficient DR program may intercept significant wind curtailment, and consequent decrease of emissions.

On this basis, in this thesis, DR programs are prioritized according to the ISO's economic, technical, and environmental desires by means of Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method. The price elasticity of demand and customer's participation level in DR programs are two critical factors which have significant impression on DR effectiveness. Hence, the sensitivity of each DR program to these vital factors are evaluated as it reveals an interpretation of how ISO can select a proper DR strategy regarding the DR programs dependency on elasticity and customer acceptance.

5.2 Multi Criteria Decision Making Procedure

DR programs portfolio contains versatile DR programs including TBRDRPs, IBDRPs and the combinational ones. It is very crucial for the ISO to find the most effective DR program by simultaneous consideration of its economic, technical and environmental desires.

Economically, DR programs have different impacts on system operation cost. From technical point of view, DR programs are required to cope with the uncertainty of wind generation so that reduce the conventional fleet ramp need. In addition, DR may lead to facilitate wind power integration and therefore decrease the emissions from environmental perspective.

The technical and environmental criteria are conventional unit's ramp need and total pollutant emission as formulated in Equation 5.1 and Equation 5.2, respectively. Note that two most popular pollutants including SO_2 and NO_x are considered to conduct emission calculation [174].

$$RampNeed = \sum_{i=1}^{NG}\sum_{w=1}^{NW}\sum_{t=1}^{NT}\rho_w \left|P_{i,w,t} - P_{i,w,t-1}\right| \tag{5.1}$$

$$Emission = \sum_{t=1}^{NT}\sum_{i=1}^{NG}\left[\left(IE_i^{SO_2} + IE_i^{NO_x}\right)U_{i,t} + \sum_{t=1}^{NT}\rho_w\left(P_{i,w,t}e_i^{SO_2} + P_{i,w,t}e_i^{NO_x}\right)\right] \tag{5.2}$$

The prioritizing of DR programs is carried out from ISO's point of view considering the above mentioned criteria using TOPSIS. To this end, the economic, technical, and environmental criteria are weighted by means of entropy method [175]. First of all, it is necessary to form a decision matrix so that its elements represent the performance of the a^{th} alternative with respect to the k^{th} criteria $\chi_{a,k}$.

The calculated elements must be normalized according to Equation 5.3. Note that, in Equation 5.3, NA it is the number of alternatives (different DR programs in this thesis). Then, for the k^{th} criteria the EE_k parameter could be formulated as Equation 5.4 [175]. Finally, the deviation degree and the weight for each criterion can be obtained through Equation 5.5 and Equation 5.6, respectively.

$$P_{a,k} = \frac{\chi_{a,k}}{\sum_{a=1}^{NA} \chi_{a,k}} \tag{5.3}$$

$$EE_k = -\left(LnNA\right)^{-1} \sum_{a=1}^{NA} [P_{a,k} \times LnP_{a,k}] \qquad 0 \le EE_k \le 1 \tag{5.4}$$

$$dd_k = 1 - EE_k \tag{5.5}$$

$$W_k = \frac{dd_k}{\sum_{k=1}^{NK} dd_k} \tag{5.6}$$

TOPSIS is a well-known method for prioritizing that simultaneously calculates the distance of each alternative from both the ideal and the non-ideal solutions. For this purpose, the elements of decision matrix should be normalized at first using Equation 5.7, and then, the weighted normalized decision matrix can be obtained as formulated in Equation 5.8.

Afterward, the ideal and non-ideal solutions for each criterion are determined with respect to its correlation with the ISO objectives as observed in Equation 5.9. It is notable that the considered economic, technical, and environmental attributes in this thesis have a negative correlation such that their lower values are closer to ideal and vice versa.

The distance of each alternative from ideal and non-ideal solutions is accounted by means of Equation 5.10 and Equation 5.11, respectively. Finally, the mean distance between each alternative and non-ideal solution is considered as decision criterion as defined in Equation 5.12. The higher obtained value for C_a indicates the better alternative.

$$r_{a,k} = \frac{\chi_{a,k}}{\sqrt{\sum_{a=1}^{NA} \chi_{a,k}^2}} \tag{5.7}$$

$$V_{a,k} = W_k \times r_{a,k} \tag{5.8}$$

$$\begin{aligned} V_k^{+} &= \left(\max V_{a,k} \left| k \in K^{+} \right|, (\min V_{a,k} \left| k \in K^{-\blacklozenge} \right|\right) \quad a = 1,....NA \\ V_k^{-} &= \left(\min V_{a,k} \left| k \in K^{+} \right|, (\max V_{a,k} \left| k \in K^{-\blacklozenge} \right|\right) \quad a = 1,...NA \end{aligned} \tag{5.9}$$

$$S_a^{+} = \sqrt{\sum_{k=1}^{NK} (V_{a,k} - V_k^{+})^2} \qquad a = 1,.....NA \tag{5.10}$$

$$S_a^{-} = \sqrt{\sum_{k=1}^{NK} (V_{a,k} - V_k^{-})^2} \qquad a = 1,.....NA \tag{5.11}$$

$$C_a = \frac{S_a^-}{S_a^+ + S_a^-} \qquad\qquad 0 \le C_a \le 1 \tag{5.12}$$

In the proposed model, the objective function minimizes the operation cost of system subject to relative constraints from the ISO's point-of-view. Indeed, all parts are the operation cost presented by the two-stage stochastic model. In the two-stage stochastic model, the first stage represents the day-ahead session and the second stage represents the real-time session. The schematic diagram of the proposed strategy is illustrated below. In fact, a conceptual diagram beside an appropriate flowchart to state the solution method and decision variables are presented in Figure 5.1.

5.3 Numerical Results

In order to examine the performance of the proposed model, several numerical studies have been conducted on the modified IEEE Reliability Test System (RTS 24-bus) [176]. The conventional generation install capacity is 3105 MW while the system peak load is equal to 2850 MW. The offered cost of generating units in energy and up/down reserve markets have been extracted from [174] as shown in Table 5.1.

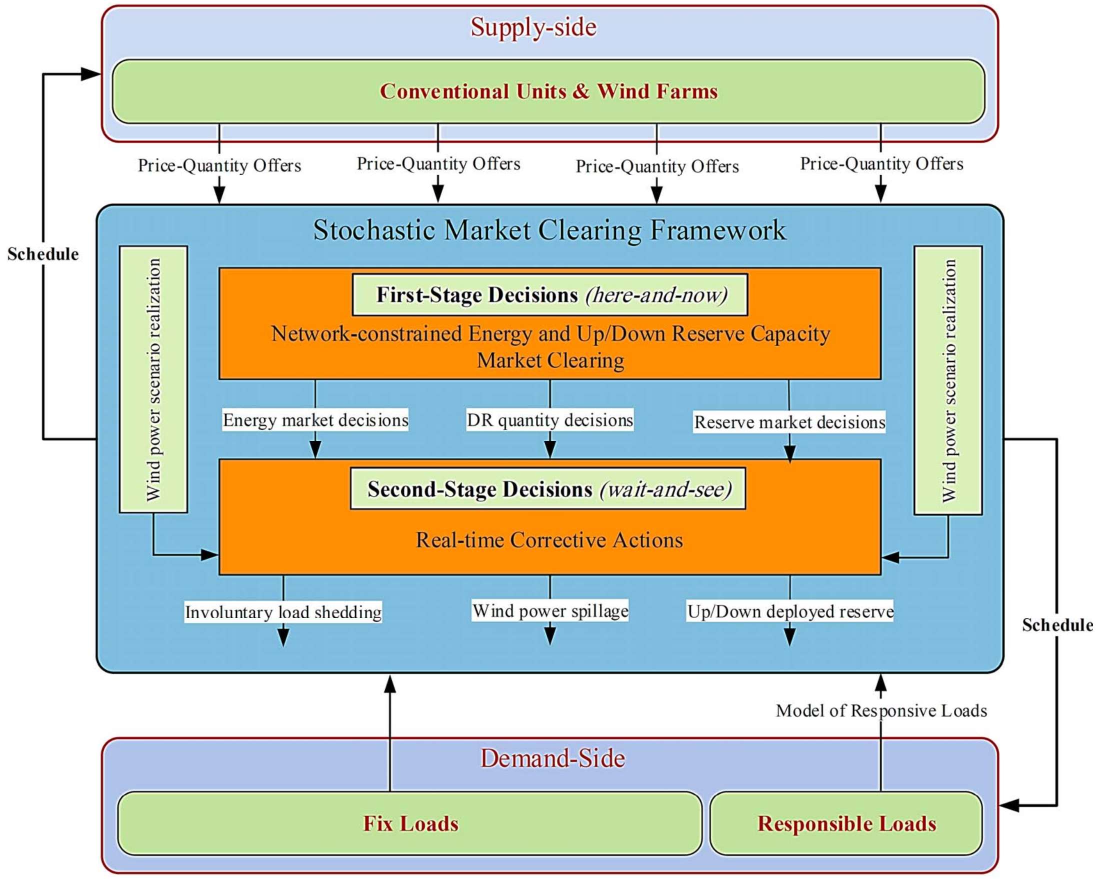


Figure 5.1- Schematic diagram of the proposed strategy.

The emission function slopes and the start-up emission of conventional units are the same as those for corresponding unit fuel cost curves, all multiplied by conversion factors of 0.2 and 0.5 for SO_2 and NO_x emission, respectively [174].

There are 6 wind farms; each has 200 MW install capacity, located at buses 1, 4, 6, 18, 21, and 22, as shown in Figure 5.2. Without loss of generality, DR is assumed to be uniform among all buses in this thesis. In this regard, the potential of DR implementation is considered to be 10% of the total load at each load point. Also, the values of self and cross price elasticity of demand and low-load, off-peak, and peak time intervals are illustrated in Table 5.2 [21].

The initial electricity price before DR implementation is 15 $/MWh equal to the average of hourly electricity prices when there is no DR. The considered DR portfolio includes several TBRDRPs, IBDRPs, and combinational DR programs which are widely used programs in power market as indicated in Table 5.3.

The model has been solved using CPLEX 12.5.0 under GAMS software. The impacts of different types of DR programs implementation on system load profile is shown in Figure 5.3. Approximately, all types of the programs try to decrease the load level at peak period while increase the load level at low-load hours and consequently provide a flatter load profile. This will not only remove the strain on conventional generation units but also support the integration of wind power to power system.

In order to examine the performance of DR programs, the ISO decision criteria including economic, environmental, and technical objectives have been reported in Table 5.4.

Table 5.1- Generation units cost data [174].

	# Generation Unit							
	i_1-i_5	i_6-i_9	i_{10}-i_{13}	i_{14}-i_{16}	i_{17}-i_{20}	i_{21}-i_{23}	i_{24}	i_{25}-i_{26}
SC_i ($)	87.40	15.00	715.20	575.00	312.00	1018.90	2298.00	0
MPC_i ($)	5.250	5.00	7.50	8.50	6.25	15.00	20.00	0
$C_{i,t,1}^{G\_Eng}$ ($/MWh)	23.41	29.58	11.46	18.60	9.92	19.20	10.08	5.31
$C_{i,t,2}^{G\_Eng}$ ($/MWh)	23.78	30.42	11.96	20.03	10.25	20.32	10.66	5.38
$C_{i,t,3}^{G\_Eng}$ ($/MWh)	26.84	42.82	13.89	21.97	10.68	21.22	11.09	5.53
$C_{i,t,4}^{G\_Eng}$ ($/MWh)	30.40	43.28	15.97	22.72	11.26	22.13	11.72	5.66
$C_{i,t}^{G\_UC}$ ($/MW)	10.44	14.61	5.33	8.33	4.210	8.29	4.35	2.19
$C_{i,t}^{G\_DC}$ ($/MW)	10.44	14.61	5.33	8.33	4.210	8.29	4.35	2.19
$C_{i,t}^{G\_UE}$ ($/MWh)	26.11	36.53	13.32	20.76	10.53	20.72	10.89	5.47
$C_{i,t}^{G\_DE}$ ($/MWh)	26.11	36.53	13.32	20.76	10.53	20.72	10.89	5.47

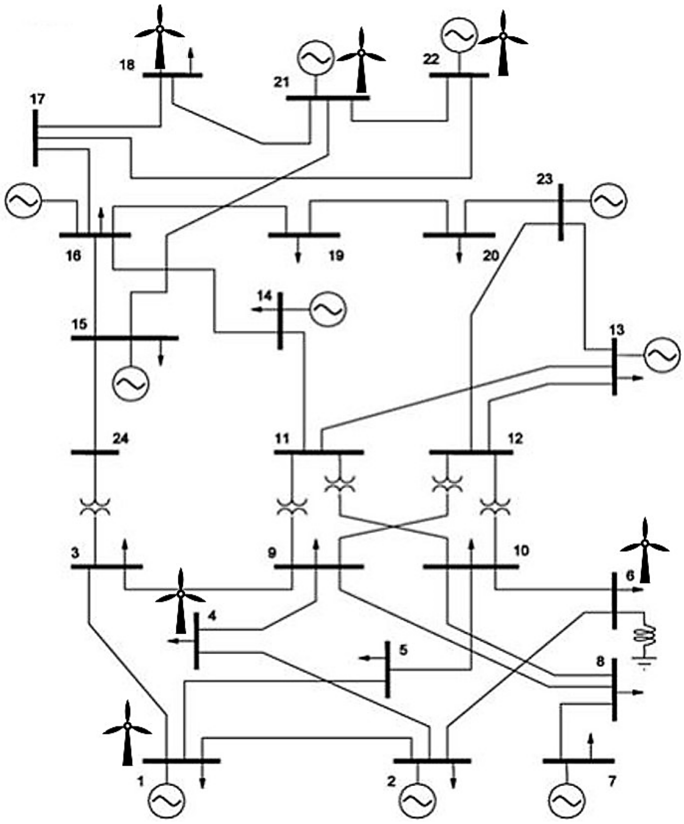


Figure 5.2- Modified IEEE Reliability Test System (RTS 24-bus).

Table 5.2- Piece elasticity values [21].

	Peak	Off-peak	Low-load	Period
Peak	-0.10	0.016	0.012	17:00-24:00
Off-peak	0.016	-0.10	0.010	09:00-16:00
Low-load	0.012	0.010	-0.10	01:00-8:00

As observed, although C7 has an impressive impact on reducing operation cost, pollutant emission and generation unit's ramp need reduction. For instance, the ramp need is decreased by 12% as a consequence of C7. According to the obtained results, it can be concluded that different DR programs have distinct and partly conflicting impacts on decision criteria.

In order to compare the effectiveness of various DR programs, the considered cases (C1-C20) are prioritized by means of TOPSIS. The obtained weights for operation cost, pollutant emission, and ramp need are 0.34, 0.33, and 0.33, respectively using the entropy method. The priorities have been calculated as shown in Figure 5.4. As it can be seen, C7 has the highest priority among all DR programs. Afterward, the next ranks are associated with C2, C6 and C10 with a negligible difference. The obtained results reveal that RTP program has a key role in satisfying ISO objectives since RTP is a common program in the first three high priority cases.

Moreover, as shown in Figure 5.4, it seems that the IBDRPs cannot be perfect alternatives by its own due to the fact that these programs have the lowest priority in comparison with other DR programs.

The considered DR programs have different impacts on wind power spillage amounts as shown in Figure 5.5. In the case C2, the wind spillage volume has been decreased by 27.2% in comparison with case C1.

Table 5.3- DR programs portfolio statement.

DR Type	Case No.	Programs	Electricity price ($/MWh)	Incentive value at peak ($/MWh)	Penalty value at peak ($/MWh)
Base	C1	Initial load	15 flat rate	0	0
TBR	C2	TOU	5.0, 15.0, 45.0 at low-load, off-peak, and peak periods, respectively	0	0
	C3	TOU	7.5, 15.0, 30.0 at low-load, off-peak, and peak periods, respectively	0	0
	C4	TOU	10.0, 15.0, 22.5 at low-load, off-peak, and peak periods, respectively	0	0
	C5	RTP	12.0, 10.7, 10.2, 5.7, 5.4, 5.4, 5.5, 5.7, 11.1, 13.9, 15.0, 20.3, 20.3, 20.1, 20.3, 19.1, 20.6, 22.1, 22.1, 22.1, 21.9, 21.2,20.3,13.8; at 1-24h	0	0
	C6	RTP	Same as case No. C5 multiplied by 1.5	0	0
	C7	RTP	Same as case No. C6 multiplied by 2	0	0
	C8	CPP	22.5 at peak period and otherwise 15	0	0
	C9	CPP	30 at peak period and otherwise 15	0	0
	C10	CPP	45 at peak period and otherwise 15	0	0
IBDR	C11	EDRP	15 flat rate	2.500	0
	C12	EDRP	15 flat rate	5.000	0
	C13	EDRP	15 flat rate	10.000	0
	C14	I/C	15 flat rate	1.250	0.625
	C15	I/C	15 flat rate	2.500	1.250
	C16	I/C	15 flat rate	5.000	2.500
TBRDRPs + IBDRPs	C17	TOU+EDRP	7.5, 15.0, 30.0 at low-load, off-peak, and peak periods, respectively	5.000	0
	C18	RTP+EDRP	12.0, 10.7, 10.2, 5.7, 5.4, 5.4, 5.5, 5.7, 11.1, 13.9, 15.0, 20.3, 20.3, 20.1, 20.3, 19.1, 20.6, 22.1, 22.1, 22.1, 21.9, 21.2, 20.3, 13.8; at 1-24h	5.000	0
	C19	TOU+I/C	7.5, 15.0, 30.0 at low-load, off-peak, and peak periods, respectively	2.500	1.250
	C20	RTP+I/C	12.0, 10.7, 10.2, 5.7, 5.4, 5.4, 5.5, 5.7, 11.1, 13.9, 15.0, 20.3, 20.3, 20.1, 20.3, 19.1, 20.6, 22.1, 22.1, 22.1, 21.9, 21.2, 20.3, 13.8; at 1-24h	2.500	1.250

Also, it can be noted that cases C4 and C7 to C16are not appropriate options for improving wind integration. By comparing similar cases under RTP and TOU programs, it is observed that TOU is a more favorable program from wind integration point of view.

The impacts of versatile DR programs implementation on different cost terms of objective function have been demonstrated in Table 5.5. As observed, DR programs, particularly TBRDRPs, affect the cost of energy provision, significantly. Also, it is clear that most of the deployed reserve is downward due to the fact that the deployed reserve cost is negative.

In general, the involuntary load shedding is decreased as a result of DR implementation except that cases C5, C8, C12 and C16. For instance, in case C12, increment of load shedding cost is compensated through cost reduction in other terms including energy, capacity reserve, and wind spillage costs and hence, DR is totally reasonable.

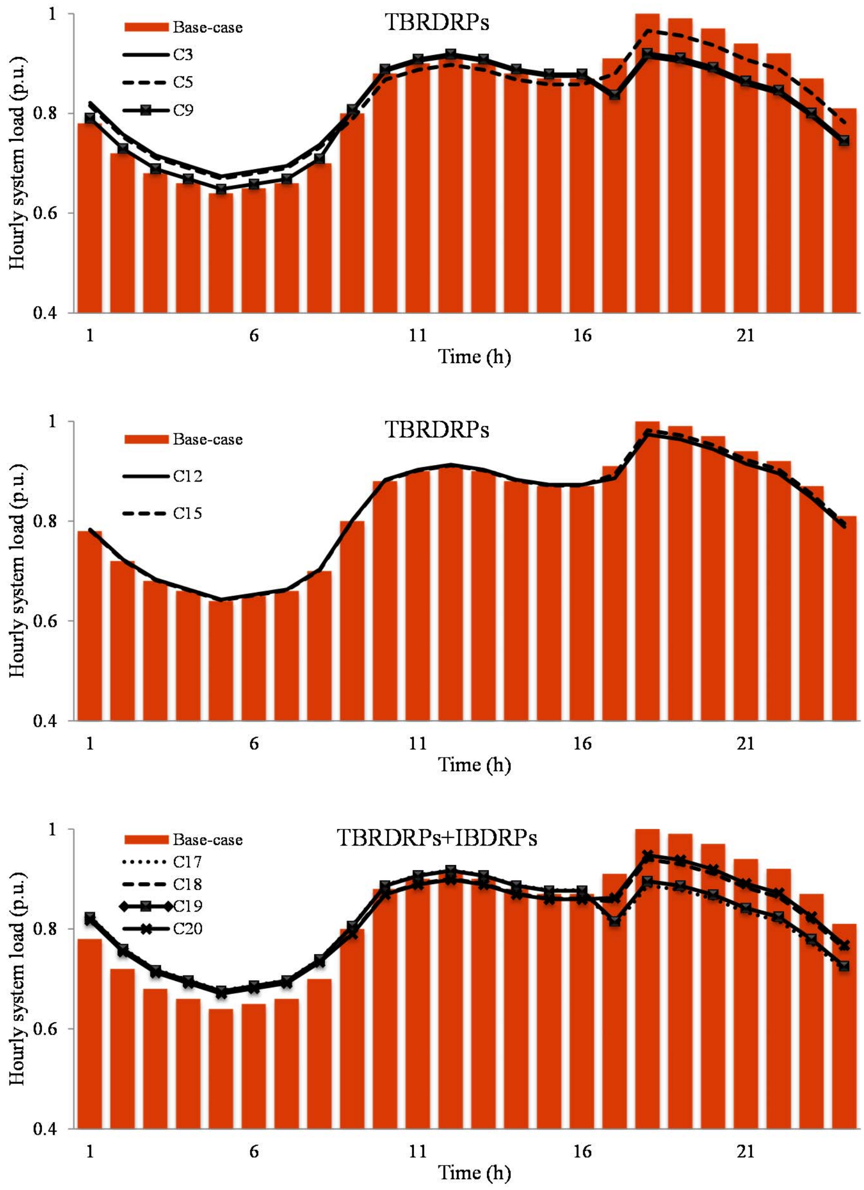


Figure 5.3- Effect of various DR programs on load curve in given cases.

Table 5.4- ISO decision criteria for 24-hour scheduling horizon.

Case No.	Flexibility Metrics		
	Operation Cost ($)	Pollutant Emission (lbs.)	Ramp Need (MW)
C1	538562	201816	4886
C2	487654	184332	4695
C3	510484	193088	4704
C4	524262	197781	4700
C5	524989	197756	4514
C6	493069	185747	4605
C7	464722	173797	4300
C8	523750	197596	4645
C9	509229	192718	4757
C10	484922	183588	4756
C11	534292	200188	4893
C12	532722	199297	4649
C13	530020	195989	4817
C14	535272	200405	4838
C15	532179	199242	4731
C16	528415	197839	4644
C17	504730	189978	4684
C18	517676	194683	4592
C19	504883	190883	4797
C20	518301	195513	4497

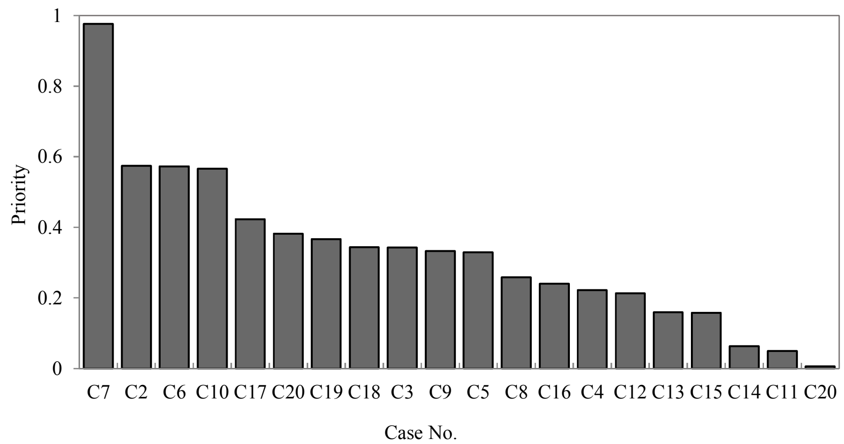


Figure 5.4- DR programs priorities.

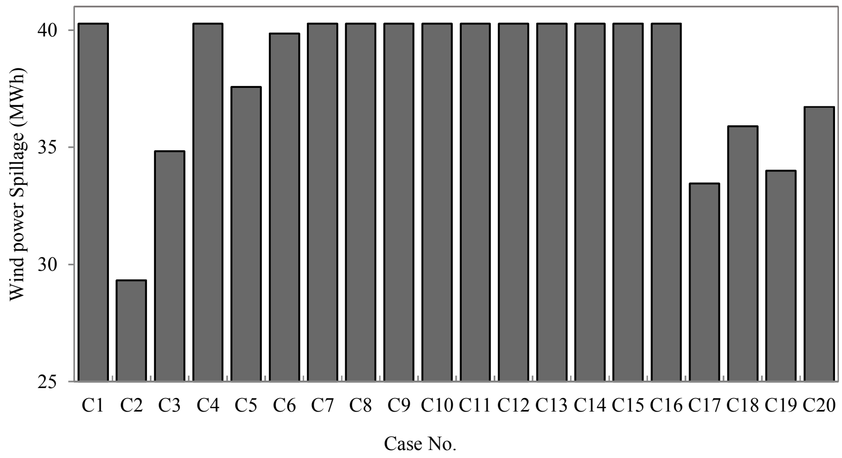


Figure 5.5- Wind spillage in the given cases.

Table 5.5- Impact of different DR programs implementation on cost terms.

Case No.	Cost Terms ($)						
	Energy	**Cap. Reserve**	**Dep. Reserve**	**Wind Spillage**	**Load Shedding**	**Incentive / Penalty**	**Total**
C1	514076	26243	-6992	1611	608	0	535546
C2	466212	26185	-6133	1173	217	0	487654
C3	488957	26502	-6646	1393	278	0	510484
C4	502941	26388	-7168	1611	490	0	524262
C5	502932	25635	-6217	1503	1136	0	524989
C6	471809	24821	-5290	1594	135	0	493069
C7	444156	24509	-5554	1611	0	0	464722
C8	502322	26254	-7122	1611	685	0	523750
C9	485065	26335	-7014	1611	352	0	506349
C10	464309	25809	-7024	1611	217	0	484922
C11	512125	26372	-7146	1611	490	840	534292
C12	506443	25566	-6804	1611	3100	2816	532722
C13	497463	26406	-7214	1611	490	11264	530020
C14	513575	26355	-7142	1611	490	383	535272
C15	510157	26479	-7192	1611	352	772	532179
C16	502788	26022	-6897	1611	1099	3792	528415
C17	480292	26482	-6473	1338	275	2816	504730
C18	493603	26204	-6659	1436	276	2816	517676
C19	482712	26439	-6481	1360	275	577	504883
C20	496454	26204	-6676	1469	273	577	518301

The impact of line flow capacity on the considered flexibility metrics have been investigated in the presence of a set of DR programs in order to explore the influences of network on the obtained results as shown in Table 5.6.

As observed, the limitation on transmission line capacity has a negative influence on the considered metrics for all the DR programs. The inherent nature of DR programs is different so that their sensitivity to price elasticity of demand as well as customer's participation level is distinct.

It is very essential for the ISO to find the sensitivity of versatile DR programs to these two important factors in order to select and implement an effective DR program. On this basis, the price elasticity values in Table 5.2 are multiplied by coefficients change from 0 to 2 applying ten equal steps.

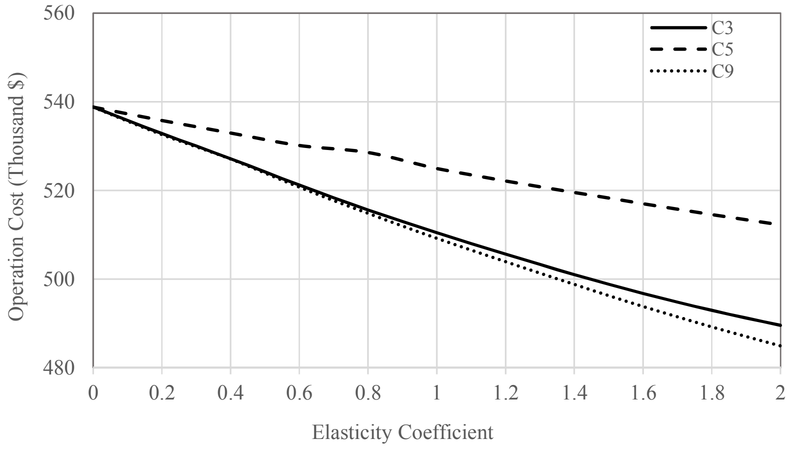
In addition, the customer's participation level is changed from 0 to 40% in a similar way. The sensitivity of several DR programs into elasticity has been investigated based on operation cost as illustrated in Figure 5.6. As observed, the changes are mainly linear. However, the ramp of the changes is different. For instance, the case C9 is the most sensitive DR program to the elasticity changes in TBRDRPs.

Also, the RTP sensitivity into elasticity changes is the lowest. Comparing Figure 5.6(a) and Figure 5.6(b) reveals that IBDRPs are less sensitive to elasticity changes in comparison with TBRDRPs. Figure 5.6(c) also indicates that combining TBRDRPs and IBDRPs increase their sensitivity to elasticity changes. The sensitivity of DR programs into customer's participation level has been investigated based on operation cost changes as represented in Figure 5.7.

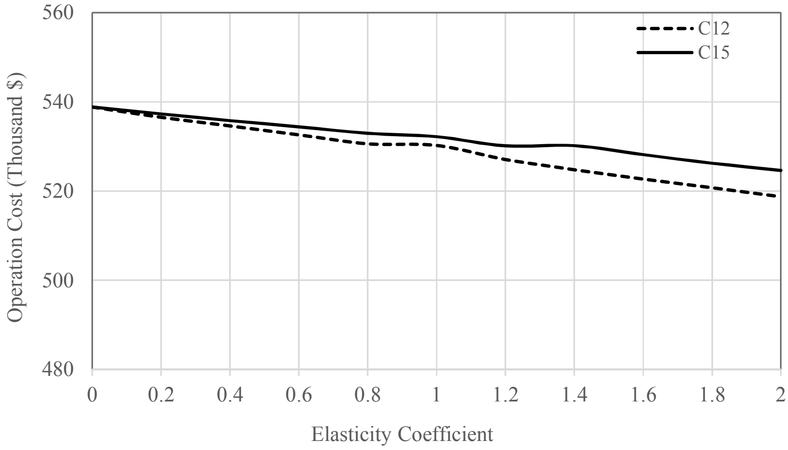
The standard deviation of variations in the operation cost as a result of changing elasticity and participation level is subsequently calculated as an index to determine the sensitivity of different DR programs. The less standard deviation devotes to the less sensitive DR program. The sensitivity of DR programs to price elasticity and participation level has been reported in Figure 5.8.

Table 5.6- Impact of line flow capacity on flexibility metrics in given DR programs.

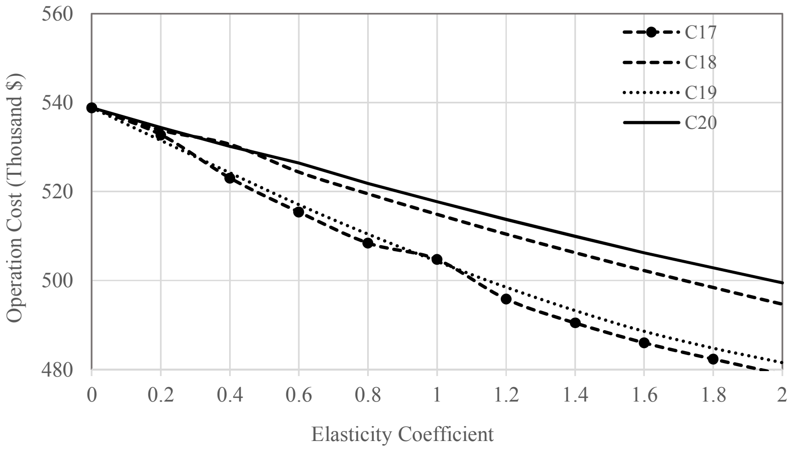
Case No.	Operation Cost ($)		Pollutant Emission (lbs.)		Ramp Need (MW)	
	Max. Line Flow	50% Max. Line Flow	Max. Line Flow	50% Max. Line Flow	Max. Line Flow	50% Max. Line Flow
C3	510484	528775	193088	196792	4704	4725
C5	524989	540878	197756	200493	4514	4861
C9	509229	526040	192718	195304	4757	4803
C12	532722	542867	199297	201157	4649	5030
C15	532179	545582	199242	201972	4731	5047
C17	504730	521300	189978	193953	4684	4929
C18	517676	532320	194683	197790	4592	4875
C19	504883	523391	190883	194770	4797	4936
C20	518301	534688	195513	198456	4497	4938



a) TBRDRPs

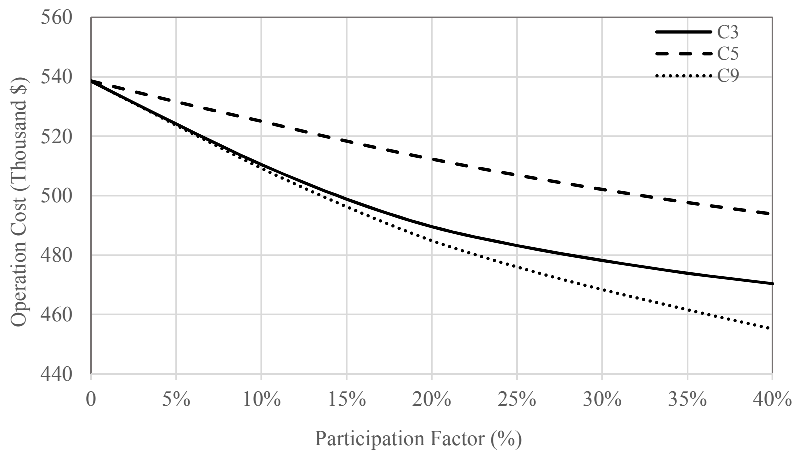


b) IBRDRPs

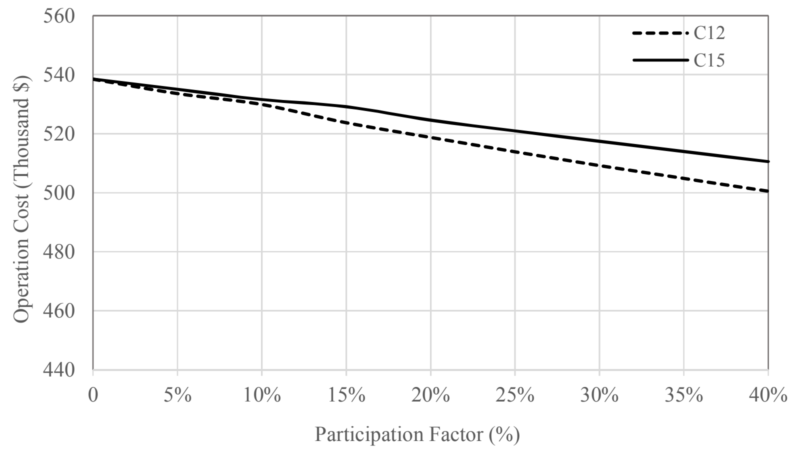


c) Combinational DRPs

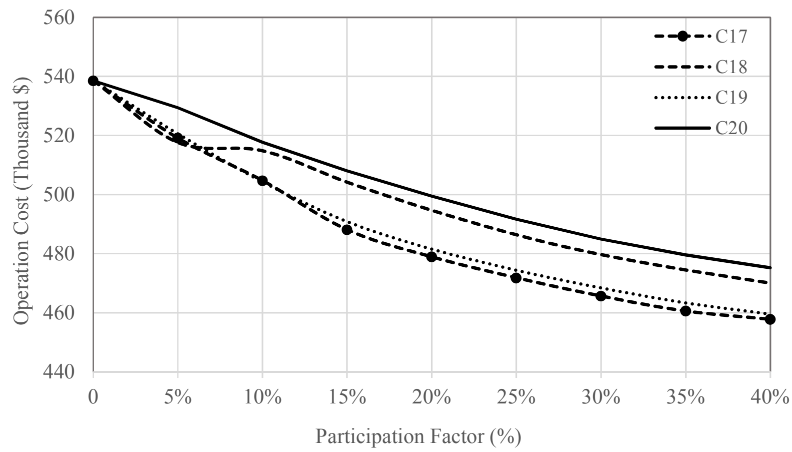
Figure 5.6- Sensitivity of operation cost into elasticity in the given cases.



a) TBRDRPs



b) IBRDRPs



c) Combinational DRPs

Figure 5.7- Sensitivity of operation cost into participation factor in the given cases.

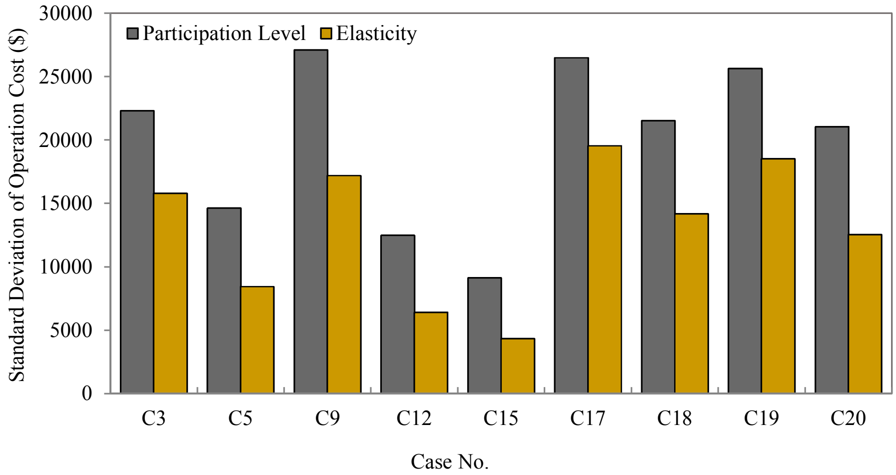


Figure 5.8- Standard deviation of operation cost with respect to elasticity and participation level in the given cases.

As shown in Figure 5.8, the sensitivity of DR programs to participation level is more than elasticity due to the fact that the standard deviation values associated with participation level are higher in all cases. Moreover, the case C15 is less sensitive in the both factors including elasticity and participation level. Afterward, case C12 has the lower sensitivity. Due to the obtained results, it can be concluded that IBDRPs are less sensitive in comparison with other types of DR programs. In addition, the most sensitive case to participation level is C9, while C17 has the highest sensitivity with respect to the elasticity.

5.4 Final Considerations

This chapter provide a stochastic network-constrained energy and reserve market clearing model incorporating a comprehensive DR program's portfolio to precisely evaluate the performance of different types of DR programs, including TBRDRPs, IBDRPs, and combinational DR programs on facilitating wind power integration. The proposed model investigated the effectiveness of DR programs taking into account economical, technical, and environmental preferences of ISOs applying a multi criteria decision making approach, specifically the TOPSIS technique. The key findings of several conducted analyses are summarized below:

- Even if the results may be case-sensitive, in the studied network the RTP program had a key role in meeting the ISO objectives since RTP was in the top three ranked programs;
- IBDRPs are not perfect options by their own, while their combination with TBRDRPs, particularly RTP, may lead to remarkable achievements;
- The sensitivity of DR programs to the participation level is more than the elasticity of demand.
- The IBDRPs are less sensitive into the participation level and price elasticity of demand in comparison with other types of DR programs.

Chapter 6

6. Conclusions, Directions for Future Work and Contributions

In this chapter, the main conclusions of the thesis are highlighted on the basis of answering the research questions that constituted the main motivation of this research. The limitations of the work in this thesis, and some directions of future work are also discussed. Finally, the contributions of this work are highlighted by presenting the set of publications in journals, book chapters or conference proceedings of high standard (IEEE), leading to this thesis work.

6.1 Main Conclusions

The main conclusions drawn from the thesis work, pertaining to the research questions presented in Section 1.2, are summarized as follows. For the sake of clarity, the research questions are reproduced here.

How can we manage the operation and propose useful tools to the independent system operator employing demand response programs despite the whole uncertainties surrounding the market, especially pertaining to the wind farms?

This thesis proposed a stochastic network-constrained energy and reserve market clearing model incorporating a comprehensive DR program's portfolio to precisely evaluate the performance of different types of DR programs, including TBRDRPs, IBDRPs, and combinational DR programs on facilitating wind power integration. The proposed model investigated the effectiveness of DR programs taking into account economical, technical, and environmental preferences of ISOs applying a multi criteria decision making approach, specifically the TOPSIS technique.

What are the impacts of proposed time/price or incentive based demand response programs and their diverse tariffs, on the amount of wind spillage and involuntary load shedding considering the uncertainty of the wind units?

The considered DR programs have different impacts on wind power spillage amounts as shown in Figure 5.5, of the last chapter. In case C2, the wind spillage volume has been decreased by 27.2%, in comparison with case C1. Also, it can be noted that cases C4 and C7 to C16 are not appropriate options for improving wind power integration.

By comparing similar cases under RTP and TOU programs, it can be observed that TOU is a more favorable program from wind integration point of view. The impacts of versatile DR programs implementation on different cost terms of the objective function have been demonstrated in Table 5.5, Chapter 5.

It is clear that most of the deployed reserve is downward due to the fact that the deployed reserve cost is negative. In general, the involuntary load shedding is decreased as a result of DR implementation, except for cases C5, C8, C12 and C16. For instance, in case C12, an increment of load shedding cost is compensated through cost reduction in other terms including energy, capacity reserve, and wind spillage costs.

What impacts of modeled time/price or incentive based demand response programs and their various tariffs have been already observed on the operation costs of the system considering the uncertainty of the wind units?

The impacts of diverse DR programs implementation on different cost terms of the objective function, as explained in Equation 4.1 of Chapter 4, have been demonstrated in Table 5.5 of Chapter 5. As observed, DR programs, particularly TBRDRPs, affect the cost of energy provision significantly. Also, it is clear that most of the deployed reserve is downward due to the fact that the deployed reserve cost is negative.

Which are the optimum tariffs among the different DR modeled programs to reach the flexible conditions of the market when there are drastic power shortages of the renewable production units or at the time of a collapse of supply and demand balance?

The impacts of different types of DR programs implementation on system load profile is shown in Figure 5.3, Chapter 5. Approximately, all types of programs try to decrease the load level at peak period while increasing the load level at low-load hours, thus consequently providing a flatter load profile.

This will not only remove the strain on conventional generation units, but also support the integration of wind power to the system. In order to examine the performance of DR programs, the ISO decision criteria, including economic, environmental, and technical objectives, has been reported in Table 5.4, Chapter 5.

As observed, although C7 has an impressive impact on reducing operation cost, pollutant emission and generation unit's ramp need reduction. For instance, the ramp need is decreased by 12% as a consequence of C7. According to the obtained results, it can be concluded that different DR programs have distinct and partly conflicting impacts on decision criteria.

Which DR programs among the time/price or incentive based demand response programs and their various tariffs have priority in terms of the independent system operator to satisfy the market regulator from the economic, environmental and technical points of view?

In order to compare the effectiveness of various DR programs, the considered cases (C1-C20) are prioritized by means of TOPSIS in Chapter 5 of this thesis. The priorities have been calculated as shown in Figure 5.3. As it can be seen, C7 has the highest priority among all DR programs. Afterward, the next ranks are associated with C2, C6 and C10 with a negligible difference.

The obtained results reveal that the RTP program has a key role in satisfying ISO objectives since RTP is a common program in the first three high priority cases. Moreover, as shown in Figure 5.4, it seems that the IBDRPs cannot be perfect alternatives by its own due to the fact that these programs have the lowest priority in comparison with other DR programs.

What is the relation between the increasing customer participation rate and operation cost?

The inherent nature of DR programs is different so that their sensitivity to customer's participation level is also distinct. It is very essential for the ISO to find the sensitivity of versatile DR programs to this important factor in order to select and implement an effective DR program.

On this basis, in this thesis, the customer's participation level is changed from 0 to 40%, applying ten equal steps. The sensitivity of DR programs into customer's participation level has been investigated based on operation cost changes as represented in Figure 5.7.

As observed, the changes are mainly linear. However, the ramp of the changes is different. For instance, the case C9 is the most sensitive DR program to the participation rate changes in TBRDRPs.

Also, the RTP sensitivity into participation rate changes is the lowest. Comparing Figure 5.6(a) and Figure 5.6(b) reveals that IBDRPs are less sensitive to participation rate changes in comparison with TBRDRPs. Figure 5.6(c) also indicates that combining TBRDRPs and IBDRPs increase their sensitivity to participation rate changes.

How much are the DRPs sensitivity to changing the elasticity and the participation rate of the consumers?

It is crucial for the ISO to find the sensitivity of versatile DR programs to these two important factors in order to select and implement an effective DR program. On this basis, the price elasticity values in Table 2.5 are multiplied by coefficients ranging from 0 to 2, applying ten equal steps. As discussed in detail in Chapter 5, the sensitivity of DR programs to the participation level is more than the elasticity of the demand.

6.2 Directions for Future Works

The following points may be further studied in order to broaden the understanding of the topics treated in this thesis:

- Even if the results may be case-sensitive, in the studied network the RTP program had a key role in meeting the ISO objectives since RTP was in the top three first rank programs; thus, the analysis can be conducted and focused on a wide variety of RTP programs of PBDPPs or a combination of that with other DR programs;
- In this thesis the problem has been solved through a two-stage stochastic optimization approach. It is suggested to solve also via robust optimization with results analysis;
- In this thesis, the proposed model has been implemented and analyzed in the day-ahead and the real-time energy market. It is recommended that the modeling be studied in other types of electricity markets;
- Employing other flexible options, such as EVs and energy storage, which can contribute to flexibility provision in addition to DR resources, can be considered in future works.

6.3 Relevant Contributions of the Thesis

6.3.1 Book Chapters

1. **N. Hajibandeh**, M. Shafie-khah, S. Talari, J.P.S. Catalão, "The impacts of demand response on the efficiency of energy markets in the presence of wind farms", in: Technological Innovation for Smart Systems, Eds. L.M. Camarinha-Matos, M. Parreira-Rocha, J. Ramezani, DoCEIS 2017, IFIP AICT 499, **SPRINGER**, Heidelberg, Germany, ISBN: 978-3-319-56076-2, pp. 287-296, May 2017.
   http://dx.doi.org/10.1007/978-3-319-56077-9_28

6.3.2 Publications in Peer-Reviewed Journals

1. **N. Hajibandeh**, M. Shafie-khah, S. Talari, S. Dehghan, N. Amjady, S.J.P.S. Mariano, J.P.S. Catalão, "Demand response based operation model in electricity markets with high wind power penetration", **IEEE Transactions on Sustainable Energy**, 2019 (forthcoming).
   https://doi.org/10.1109/TSTE.2018.2854868

2. **N. Hajibandeh**, M. Ehsan, S. Soleymani, M. Shafie-khah, J.P.S. Catalão, "Prioritizing the effectiveness of a comprehensive set of demand response programs on wind power integration", **International Journal of Electrical Power & Energy Systems (ELSEVIER)**, Vol. 107, pp. 149-158, May 2019
https://doi.org/10.1016/j.ijepes.2018.11.024

3. **N. Hajibandeh**, M. Shafie-khah, G.J. Osório, J. Aghaei, J.P.S. Catalão, "A heuristic multi-objective multi-criteria demand response planning in a system with high penetration of wind power generators", **Applied Energy (ELSEVIER)**, Vol. 212, pp. 721-732, February 2018.
https://doi.org/10.1016/j.apenergy.2017.12.076

4. **N. Hajibandeh**, M. Ehsan, S. Soleymani, M. Shafie-khah, J.P.S. Catalão, "The mutual impact of demand response programs and renewable energies: a survey", **Energies**, Vol. 10, No. 9, pp. 1-18, September 2017.
http://dx.doi.org/10.3390/en10091353

6.3.3 Publications in International Conference Proceedings

1. **N. Hajibandeh**, M. Shafie-khah, M. Ehsan, J.P.S. Catalão, "Optimizing nodal demand response in the day-ahead electricity market within a smart grid infrastructure", in: Proceedings of the 16th **IEEE** International Conference of Industrial Informatics – ***INDIN 2018***, Porto, Portugal, USB flash drive, July 18-20, 2018.
https://doi.org/10.1109/INDIN.2018.8472049

2. **N. Hajibandeh**, M. Ehsan, S. Soleymani, M. Shafie-khah, J.P.S. Catalão, "Modeling price- and incentive-based demand response strategies in the renewable-based energy markets", in: Proceedings of the 17th **IEEE** International Conference on Environment and Electrical Engineering – ***EEEIC 2017***, Milan, Italy, USB flash drive, 6-9 June, 2017.
https://doi.org/10.1109/EEEIC.2017.7977701

3. **N. Hajibandeh**, M. Shafie-khah, G.J. Osório, J.P.S. Catalão, "A new approach for market power detection in renewable-based electricity markets", in: Proceedings of the 17th **IEEE** International Conference on Environment and Electrical Engineering – ***EEEIC 2017***, Milan, Italy, USB flash drive, 6-9 June, 2017.
https://doi.org/10.1109/EEEIC.2017.7977699

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