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Optimal Demand Response Strategy in Electricity Markets through Bi-level Stochastic Short-Term Scheduling

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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 tecnologia atual na monitorização inteligente, incluindo a *Internet of Things* (IoT), permite que a rede elétrica ao nível da transporte e distribuição faça uso de programas de *demand response* (DR) para garantir a operação segura e económica dos sistemas de energia. A liberalização e a reestruturação da indústria dos sistemas de energia elétrica também promovem a gestão do lado da procura de forma otimizada.

Os impactes da implementação de DR no mercado elétrico podem ser expressos pelo conceito de agregadores de DR (DRAs), sendo a *interface* entre o lado da oferta e o lado da procura de energia elétrica. Vários mercados, como os mercados diário e em tempo real, são estudados visando a gestão otimizada do ponto de vista *do Independent System Operator* (ISO) ou do *Distribution System Operator* (DSO).

Para atingir os objetivos propostos, modelos de otimização em um ou dois níveis podem ser desenvolvidos. O comportamento das fontes de energia renováveis dependentes do clima, como a produção de energia eólica e fotovoltaica que acarretam incerteza, é modelado pelo método de simulação de Monte Carlo. Ainda, *two-stage stochastic programming* é aplicada para minimizar o custo de operação.

Os resultados deste estudo demonstram a importância de considerar todos os participantes efetivos no mercado, como DRAs e clientes finais, no custo de operação. Ainda, considerando a incerteza no modelo beneficia os operadores da rede na redução de custos, capacitando a resiliência e fiabilidade da rede.

Palavras Chave

Otimização em dois níveis; *Demand response*; Rede de distribuição e transporte; Mercado elétrico; Fontes de energia renováveis.

Abstract

Current technology in the smart monitoring including Internet of Things (IoT) enables the electricity network at both transmission and distribution levels to apply demand response (DR) programs in order to ensure the secure and economic operation of power systems. Liberalization and restructuring in the power systems industry also empowers demand-side management in an optimum way.

The impacts of DR scheduling on the electricity market can be revealed through the concept of DR aggregators (DRAs), being the interface between supply side and demand side. Various markets such as day-ahead and real-time markets are studied for supply-side management and demand-side management from the Independent System Operator (ISO) viewpoint or Distribution System Operator (DSO) viewpoint.

To achieve the research goals, single or bi-level optimization models can be developed. The behavior of weather-dependent renewable energy sources, such as wind and photovoltaic power generation as uncertainty sources, is modeled by the Monte-Carlo Simulation method to cope with their negative impact on the scheduling process. Moreover, two-stage stochastic programming is applied in order to minimize the operation cost.

The results of this study demonstrate the importance of considering all effective players in the market, such as DRAs and customers, on the operation cost. Moreover, modeling the uncertainty helps network operators to reduce the expenses, enabling a resilient and reliable network.

Keywords

Bi-level programming; Demand response; Distribution and transmission network; Electricity market; Renewable energy sources.

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List of Symbols

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Chapter3

Indices (sets) and abbreviations

DBK	Set of demand response offers between DR aggregator and customer.
DRK	Set of demand response offers between ISO and DR aggregator.
$g\ (NG)$	Index (set) of generating units.
gen	Generator units.
$k\ (NK)$	Index (set) of demand response offers.
$l\ (NL)$	Index (set) of transmission lines.
LC	Load curtailment option.
LS	Load shifting option.
LR	Load recovery option.
$n\ (NN)$	Index (set) of nodes.
$s\,(NS)$	Index (set) of scenarios.
$scen$	Superscripts for wind scenarios.
$shed$	Superscripts for load shedding.
$spill$	Superscripts for wind spillage.
$t\,(NT)$	Index (set) of hours.
TC, TS, TR	Set of times for load curtailment, shift and recovery options.
$\hat{X} \in LC, LS, LR$	Superscripts for LC and LS and LR.

Parameters

C_{tg}^{gen}	Production cost of generator units.
$C_{tg}^{up}, C_{tg}^{down}$	Up/down reserve cost of generator units.
$C_{g}^{strt.up}, C_{g}^{sht.dwn}$	Generator start-up/shut-down cost.
Cs_{tns}^{spill}	Wind spillage cost per scenario.
$Cs_{tgs}^{up}, Cs_{tgs}^{down}$	Up/down reserve cost per scenario.
Cs_{tns}^{voll}	Value of loss of load per scenario.
$DR_{tnk}^{Cost,\hat{X}}, DB_{tnk}^{Cost,\hat{X}}$	Cost of offer k from demand response option $\hat{X}$.
$DRK_{tnk}^{Min,\hat{X}}, DBK_{tnk}^{Min,\hat{X}}$	Minimum offer k from demand response option $\hat{X}$.

$DRK_{tnk}^{Max,\hat{X}}, DBK_{tnk}^{Max,\hat{X}}$	Maximum offer k from demand response option $\hat{X}$.
$LCD_{nk}^{\hat{X},\min}, LCD_{nk}^{\hat{X},\max}$	Min/max time for offer k from demand response option $\hat{X}$.
LD_{tn}	Forecasted load.
$MC_{nk}^{\hat{X}}$	Maximum number of calling DR option $\hat{X}$ per day.
$pf_l^{\max}, pf_l^{\min}$	Maximum/minimum transmission line capacity.
$P_g^{\max}, P_g^{\min}$	Maximum and minimum capacity of generating units.
$R_g^{\max,up}, R_g^{\max,down}$	Maximum up/down reserve.
Rmp_g^{up}, Rmp_g^{dwon}	Maximum ramp-up/-down.
X_{nl}	Transmission lines inductance.

Binary variables

u, y, z	Binary variables for on/off, start-up and shut-down status.
ub	On/off for demand response offers from DR aggregator viewpoint.

Variables

$DRK^{\hat{X}}, DBK^{\hat{X}}$	Demand response scheduling for demand response option $\hat{X}$.
P	Thermal power generation.
pf, pfs	Power line flows day-ahead/balancing.
$R_{tg}^{up}, R_{tg}^{down}$	Up/down reserve of units.
$Rs_{tgs}^{up}, Rs_{tgs}^{down}$	Up/down reserve of units for scenarios.
W	Wind power generation.
θ	Voltage angle.

Chapter 4

Indices and sets

g (NG)	Thermal generators.
k (NK)	Offers of DR.
l (NL)	Branches.
n (NN)	Buses.
s (NS)	Real-time scenarios.
t (NT)	Time.

Abbreviations and superscripts

gen	Thermal Generators.
$scen$	Wind scenarios superscript.

$shed$	Load shedding superscript.
$spill$	Wind spillage superscript.
TC, TS, TR	Time sets dedicated to load curtailment, shifting and recovery, respectively.
$\hat{X}$	LC, LS, and LR.

Parameters

C_{tg}^{gen}	Thermal generation units cost.
$C_{tg}^{up}, C_{tg}^{down}$	Up and down thermal generators reserve cost, respectively.
$C_{g}^{strt.up}, C_{g}^{sht.dwn}$	Start-up/shut-down cost for thermal generators.
Cs_{tns}^{spill}	Cost of wind spillage for each scenario.
$Cs_{tgs}^{up}, Cs_{tgs}^{down}$	Cost of up/down reserve for each scenario.
Cs_{tns}^{voll}	Value of loss of load for each scenario.
$DR_{tnk}^{Cost,\hat{X}}, DRs_{tnk}^{Cost,\hat{X}}$	Cost of offering DR option $\hat{X}$ for offer k in day-ahead and in real-time market.
$DRK_{tnk}^{Min,\hat{X}}, DRKs_{tnk}^{Min,\hat{X}}$	Minimum possible DR option $\hat{X}$ for offer k in day-ahead and real-time market.
$DRK_{tnk}^{Max,\hat{X}}, DRKs_{tnk}^{Max,\hat{X}}$	Maximum possible DR option $\hat{X}$ for offer k in day-ahead market and real-time market.
$LCD_{nk}^{\hat{X},\min}, LCD_{nk}^{\hat{X},\max}$	Min/max possible time for offer k to be available from DR option $\hat{X}$.
LD_{tn}	Total Forecasted load at each hour for each bus.
$MC_{nk}^{\hat{X}}, MCs_{nk}^{\hat{X}}$	Maximum possible number of calling DR for each day and each scenario per day.
$pf_{l}^{\max}, pf_{l}^{\min}$	Maximum/minimum branch capacity.
$P_{g}^{\max}, P_{g}^{\min}$	Maximum/minimum capacity of thermal generators.
$R_{g}^{\max,up}, R_{g}^{\max,down}$	Maximum up/down reserve of thermal generators.
$Rmp_{g}^{up}, Rmp_{g}^{dwon}$	Maximum ramp-up and ramp-down of thermal generators.
X_{nl}	Reactance of branches.

Binary variables

u, y, z	On/off, start-up and shut-down states for the day-ahead market.
us, ys, zs	On/off, start-up and shut-down states for the real-time market.

Variables

$CDR^{\hat{X}}, CDRs^{\hat{X}}$	Total cost of DR scheduling for day-ahead and real-time market.
$DRK^{\hat{X}}, DRKs^{\hat{X}}$	DR scheduling in day-ahead and real-time market for DR option $\hat{X}$.
P	Production of Thermal power generators.
pf, pfs	Load flows for day-ahead/real-time market.

$R_{tg}^{up}, R_{tg}^{down}$	Up/down reserve of thermal generators.
$Rs_{tgs}^{up}, Rs_{tgs}^{down}$	Up and down reserves of thermal generators for scenarios.
θ	Voltage angle.
W	The production of wind generators.

Chapter 5

Indices (sets) and abbreviations

DBK	Set of demand response offers between DR aggregator and customer.
DRK	Set of demand response offers between ISO and DR aggregator.
$g \ (NG)$	Index (set) of generating units.
gen	Generator units.
$k \ (NK)$	Index (set) of demand response offers.
$l \ (NL)$	Index (set) of transmission lines.
LC	Load curtailment option.
LS	Load shifting option.
LR	Load recovery option.
$n \ (NN)$	Index (set) of nodes.
$s \ (NS)$	Index (set) of scenarios.
$scen$	Superscripts for wind scenarios.
$shed$	Superscripts for load shedding.
$spill$	Superscripts for wind spillage.
$t \ (NT)$	Index (set) of hours.
TC, TS, TR	Set of times for load curtailment, shift and recovery options.
$\hat{X} \in LC, LS, LR$	Superscripts for LC and LS and LR.

Parameters

C_{tg}^{gen}	Production cost of generator units.
$C_{tg}^{up}, C_{tg}^{down}$	Up/down reserve cost of generator units.
$C_{g}^{strt.up}, C_{g}^{sht.dwn}$	Generator start-up/shut-down cost.
Cs_{tns}^{spill}	Wind spillage cost per scenario.
$Cs_{tgs}^{up}, Cs_{tgs}^{down}$	Up/down reserve cost per scenario.
Cs_{tns}^{voll}	Value of loss of load per scenario.
$DR_{tnk}^{Cost,\hat{X}}, DB_{tnk}^{Cost,\hat{X}}$	Cost of offer k from demand response option $\hat{X}$.
$DRK_{tnk}^{Min,\hat{X}}, DBK_{tnk}^{Min,\hat{X}}$	Minimum offer k from demand response option $\hat{X}$.

$DRK_{tnk}^{Max,\hat{X}}, DBK_{tnk}^{Max,\hat{X}}$	Maximum offer k from demand response option $\hat{X}$.
$LCD_{nk}^{\hat{X},\min}, LCD_{nk}^{\hat{X},\max}$	Min/max time for offer k from demand response option $\hat{X}$.
LD_{tn}	Forecasted load.
$MC_{nk}^{\hat{X}}$	Maximum number of calling DR option $\hat{X}$ per day.
$pf_l^{\max}, pf_l^{\min}$	Maximum/minimum transmission line capacity.
$P_g^{\max}, P_g^{\min}$	Maximum and minimum capacity of generating units.
$R_g^{\max,up}, R_g^{\max,down}$	Maximum up/down reserve.
Rmp_g^{up}, Rmp_g^{dwon}	Maximum ramp-up/-down.
X_{nl}	Transmission lines inductance.

Binary variables

u, y, z	Binary variables for on/off, start-up and shut-down status.
ub	On/off for demand response offers from DR aggregator viewpoint.

Variables

$CRK^{\hat{X}}, CBK^{\hat{X}}$	Total cost of demand response scheduling for demand response option $\hat{X}$.
$DRK^{\hat{X}}, DBK^{\hat{X}}$	Demand response scheduling for demand response option $\hat{X}$.
P	Thermal power generation.
pf, pfs	Power line flows day-ahead/balancing.
$R_{tg}^{up}, R_{tg}^{down}$	Up/down reserve of units.
$Rs_{tgs}^{up}, Rs_{tgs}^{down}$	Up/down reserve of units for scenarios.
W	Wind power generation.
θ	Voltage angle.

Relevant Acronyms

DR	Demand response.
DRA	Demand response aggregators.
DRP	Demand response programs.
DRX	Demand response exchange market.
DSO	Distribution system operator.
EMS	Energy management systems.
IoT	Internet of things.
ISO	Independent system operator.
Genco	Generation company.
LC	Load curtailment.
LS	Load shifting.
LR	Load recovery.
MILP	Mixed-integer linear programming.
MINLP	Mixed-integer non-linear programming.
MCS	Monte-Carlo simulation.
PV	Photovoltaic.
RES	Renewable energy sources.
SCUC	Security constrained unit commitment.
WF	Wind farm.
WPG	Wind power generation.

Chapter 1

1 Introduction

1.1 Background

Since the perception of demand side participation in the electricity market is being increased, a framework for demand response (DR) in electricity market should be designed. Some papers investigated possible markets for DR programs. In some studies, a special agent called DR aggregators are proposed mostly as an interface between customers and wholesale market. DR aggregators can participate in the capacity market (e. g. PJM, Ontario) and energy-only markets (e.g. ERCOT, Alberta, and Singapore)[1]. Reference [2] presents bottom-upper aggregators for appliances of residential demand-side in order for gathering reserve bids offered in day-ahead reserve market.

Reference [3] uses DR aggregator to consider technical constraints of customers in developing an optimal trading strategy in the wholesale market, whereas customer constraints are not considered in most papers like [4]–[6] in which investigates DR from market operator's perspective. Some modeling strategies for energy markets are offered in [7] in which DR aggregators offer customers various contracts for an hourly reduction in order to determine optimal DR in the day-ahead market. DR aggregators can even participate in balance market as well, for example, DR aggregator schedules thermal heating loads based on day-ahead price; however, conducts DR in balance market through bonus price in [8].

Moreover, bilateral forward contracts, which are based on fixed price and volume are proposed in [9], [10] without modeling the bottom-level DR programs. For bottom-level DR modeling paper [2], [7] offered a new model which consider load shifting, load curtailment and load recovery programs as DR constraints but they have not studied these DR constraints in details. DR can be traded as a commodity in DR exchange (DRX) market [11]. DRX collects both aggregated demand and individualized supply curves and then it balances the supply and demand at a common price to clear the market [12]. From retailers' point of view, [10] proposed a new DR scheme in which innovative agreements among retailers and aggregators or customers are investigated by a stochastic energy program.

Both of incentive and price-based DR programs are addressed in [13] with only considering elasticity as customer constraint. New incentive mechanism is proposed in [14] which the way customers respond to rewards is determined through game theory approach. One of the methods to cope with the uncertainty of weather-dependent renewable generation is using flexible loads as DRP.

A two-stage problem is solved in [9] to get the best DR agreements according to wind producer plans at each time period. Ref [15] presents a multi-layer agent-based model to investigate the behavior of electricity market participants in the presence of wind power producers.

For household energy management, various appliances can be modeled in DRP. Some models for space heating/cooling, water heating are presented in[16]. Air conditioning control models are in [17]. A DR model for electric heating systems is presented in [18]. The behavior of consumers to control their controllable loads is proposed in [19] through an automated energy management framework. Yet, detailed constraints of loads and appliances have not been considered in these studies.

1.2 Research Motivation and Problem Definition

With merging various smart facilities and equipment as well as Internet of Things (IoT) into different sections of power systems including generation, transmission and distribution section, consideration of DR programs is going to be much easier in order to ensure the secure, economic and less emission pollutant operation of power systems and smart cities. Meanwhile, power systems restructuring aid for implementation of optimized ways for demand-side management.

For example, the impacts of DR scheduling on both of wholesale market and the retail market can be revealed through the concept of DR aggregators, which are the connection between supply side and demand side. Various time horizon such as day-ahead, balancing, intra-day and real-time markets can be considered in energy, capacity, reserve, ancillary service, or even DRX [11] market from the Independent System Operator (ISO) viewpoint or Distribution System Operator (DSO) viewpoint.

From DSO perspective, different DR programs including load shifting, load curtailing, load recovery and load growth can be implemented in a retail market through DR aggregators. In load curtailment strategy, customers reduce their total electricity without shifting them to any other times. In load shifting, customers reschedule and shift their consumption to other time. For example, residential consumers may delay operating their appliances [7]. Customers contributing in load shifting are able to recover their reduced load in off-peak periods through load recovery program. However, they have to pay the cost for it because DR aggregators should buy surplus energy from market to recover loads [3].

In a retail market, electricity consumers can freely select a retailer to procure their required power. There is a competition among retailers to attract customers. Retailers are supposed to choose their demand side participants to apply DR for decrease the risk of market price volatility. In this way, retailers are able to set different DR contracts including, pool-based, spike-based, forward and reward DR contract.

Each contract has a specific DR amount, price and period. In pool-based contract, DR contract will be carried out only if the total DR price is less than purchasing the energy from pool market. Otherwise, the retailer has to pay specified fee as the penalty of not doing the contract. The spike-based contract is designed for retailers during high price period. It is similar to pool-based one and the difference is that it is just for a strike price which is negotiated among retailer and DR seller.

The forward contract is among retailer and aggregators or consumer for DR and it can be directly negotiated the price and size. In the reward-based the volume of reduction load will increase in a stepwise way as the retailer offer higher reward. Moreover, the retailer can purchase and sell energy from the wholesale market and the price is considered as a stochastic variable[20].

DR aggregators can also participate in the wholesale market for trading the energy either for more profit or for providing energy shortage. Running this interaction with providing enough details leads to maximization of social welfare, profit of participants and minimization of total operation cost. While, The DR aggregator is exposed to financial risks due to market price volatility, because it purchases electricity from the wholesale market at volatile rates and sells it to consumers at a flat rate.

On this basis, the aggregator can propose some DR-based contracts to customers. By reducing consumption during price spikes period, the aggregator may cover a part of these risks. On the other hand, customers can earn advantages from the DR-based contracts because of contract flexibility and reduction of their costs due to compensation of the aggregator's financial risks.

In smart grids, DR will be considered as a tradable commodity that is exchanged between DR buyers and sellers in a pool-based market called DRX and is completely separated from other electricity markets [12]. In this context, a DR aggregator is able to participate in the intraday DRX market as a buyer to amend its bid and as a seller to modify its offer in order to reduce its imbalance losses to cover its risks and avoid imbalance penalties. The aggregator as a financial agent in the power market has to compete with other players for selling and purchasing electricity.

In the business competition, the aggregator has to compete for keeping the current customers and attracting new ones. In other words, the aggregator should struggle with other market participants on three sides: offering strategy (with Gencos), bidding strategy (with retailers) and customers (also with retailers). The competition of the aggregator for customers has not been addressed in previous works. Hence, active customers as well as DR aggregators are considered for finding the best and most efficient DR programs in smart systems.

There is a classification for DR program that has two categories called incentive- and price-based DR programs. Incentive-based DR programs include Direct Load Control, Emergency Demand Response Program, Ancillary Service Demand Response and price-based programs involve Time of use, Real-time Pricing. Different possible markets are investigated for evaluation of DR programs.

Besides, high penetration of renewable energies like wind farms and photovoltaic systems causes a drop in electricity price which leads to a decrease of customer's tendency for joining in DR program. As a result, a suitable market mechanism and proper DR program are applied to cope with it. In addition, the behavior of participants including different entities and aggregators is modeled through game theory to predict market participants in the case of any changes in market regulation.

In order to model upper and bottom level of power market, it is possible to develop a bi-level optimization [15]. This environment is modeled from DR aggregator’s viewpoint. Different stochastic variables including weather-dependent renewable energy sources make an uncertain environment in power systems.

For dealing with these uncertainties, a two-stage stochastic programming is utilized in order to minimize the total operation cost. Accordingly, a short-term operation management is run for given market mechanism which can be a day-ahead market, balancing market or other proper markets.

1.3 Research Questions, Objectives and Contributions of the Thesis

This thesis presents a comprehensive analysis of DR-based power network scheduling in an uncertain environment. New analysis tools and methods are developed in this thesis that take into account the operational variability and uncertainty associated with the RES power generation while considering several electricity market players in different levels, simultaneously.

The ultimate aim of all this is to enable DSOs, ISOs and other operators to operate the network optimum, sustainable, stable and secure, using proper flexibilities, such as DR and regulation, as solutions for RES uncertainty. In other words, it is tried that applying potentials of electricity market and the relevant players, a precise strategy to operate the network is made while all network constraints are considered.

The main objectives of this thesis are:

- To investigate the-state-of-the-art survey on existence mathematical methods to model stochastic nature of renewable sources in the operation of the power system;
- To study different available approaches to cope with uncertainty of renewables generation in short-term scheduling of the power system;
- To develop an appropriate optimization method for system operator in order for a steady state operation of transmission network while all constraints are taken into account;
- To present suitable market scheme for ISOs, which are able to perform demand-side management through DRAs;

- To extract the extra potential of customers for DR implementation in real-time market in addition to day-ahead market, which has been ignored, for enhancing the stability of the transmission network and operation cost reduction;
- To develop the optimization model for distribution operator in order for DR employment through several DRAs while meeting all network constraints and customers' preference in an uncertain environment;
- To present a proper market mechanism to operate a DR-enabled distribution network with customers as active players.

In particular the following research questions are addressed:

- *What are the current solutions for modelling the stochastic nature of renewable energy resources and how to cope with the negative impacts of these sources of uncertainty on power system scheduling?*
- *What is the best market scheme to operate a power system with high penetration of wind power generation within the transmission network (wholesale market) and how to apply the potential of the DRA as an active market player?*
- *How to employ the possible extra potential of customers in the real-time market to participate in demand-side management, while their potential in day-ahead market has already been taken into account?*
- *How to apply demand-side management in the distribution network (retail market) when DRAs are responsible for DR trade-off and customers are playing an active role to benefit from this opportunity in an uncertain environment?*

The contributions of this thesis (all already published in prestigious venues) are summarized as follows:

- An overview on stochastic modeling of RESs in power system operation and the impact of different market schemes and demand-side management on accuracy increment of power system scheduling in the presence of RESs. This contribution is published in **Renewable and Sustainable Energy Reviews** (**ELSEVIER**) [21];
- A method to model the interaction of DRA and ISO to run a proper DR-enabled market to find an optimum scheduling of power system while minimizing the operation cost in an uncertain environment is proposed in a bi-level model. This contribution has been published in **IEEE Transactions on Industrial Electronics** [22].
- An expression about the possibility of DR implementation in real-time market through DRAs is presented. Unpredicted behavior or events in real-time can lead to provide the opportunity of DR implementation and the proper solution to perform this concept practically is modeled. This contribution has been presented and published in the **20th Power Systems Computation Conference (PSCC 2018)** [23].
- A comprehensive study of DR implementation in real-time market in addition to day-ahead market using the extra potential of DR-enabled customers and considering the interaction of DRAs and customers as well as ISOs are discussed. A two-stage stochastic programming is applied to run this market. This contribution has been published in **IEEE Transactions on Sustainable Energy** [24].

1.4 Methodology

The mathematical models developed in this thesis are based on well-established methods, namely, mixed-integer linear programming (MILP), bi-level 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 demand response scheduling in power 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, with Excel© used as an interface for this purpose.

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.x) and called "equation (x.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.

1.6 Organization of the Thesis

The thesis comprises seven chapters that are organized as follows.

Chapter 1 is the introductory chapter of the thesis. First, the background of the thesis is presented. Then, the research motivations and the problem definition are provided. Subsequently, the research questions and contributions of this thesis are presented. Then, the methodology used throughout the thesis is introduced, followed by the adopted notations. Finally, the chapter concludes by outlining the structure of the thesis.

In Chapter 2, a comprehensive overview of stochastic models for RESs is presented. First, stochastic analysis of renewables is conducted and mathematical solutions for stochastic modelling are presented. Then, the models that the uncertainties arising from RESs can be handled by demand side flexibilities are investigated. Finally, the role of electricity market to mitigate the stochastic nature of RESs is discussed.

In Chapter 3, a DR-enabled operation model is formulated as a multi-level, multi-stage optimization problem in order to run a pre-emptive market while considering both ISO and DRAs perspective in different levels, simultaneously. Uncertain behavior of RESs in real-time market is modeled in a two-stage programming and in a bi-level model ISO minimizes the operation cost and DRA maximizes the profit.

In Chapter 4, DR implementation in real-time market in addition to day-ahead market is modeled. A two-stage programming is formulated as MILP to consider unpredicted events in real-time which provide the extra potential for customers to participate in real-time DR. different scenarios are generated by MCS method.

Chapter 5 presents a multi-stage and multi-level optimization model in distribution network in order to find an optimum DR from DSO's perspective in one level and customers' viewpoint in another level. Stochastic nature of PVs and WPG in distribution network is modeled by scenario generation through MCS method. A proper market scheme is also offered.

Chapter 6 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).

Chapter 2

2 Stochastic Modelling of Renewable Energy Sources from Operators' Point-of-View: A Survey

High penetration of renewable energy sources, especially weather-dependent sources, has increased the power systems uncertainties. For any analysis in power systems such as planning and operation, it is essential to confront the stochastic nature of these sources in order to get much more precise results. Since operators need proper strategies and methods to decline negative effects of probabilistic behavior of renewable power generators, such as total operation cost growth, this chapter provides a review of different state-of-the-art approaches from the operator's viewpoint for handling the stochastic behavior of renewable sources.

Hence, in this chapter, three different strategies are categorized for stochastic analysis of these sources. The first strategy is mathematical modelling including stochastic dependency and independency, multi-dimensional dependence, forecast and scenarios. Afterwards, demand side management, which is one of the other approaches for dealing with these uncertainties, is investigated and different demand response programs and some methods to model them are presented.

Finally, the effect of different electricity market schemes and relevant optimization methods to mitigate the variations of renewable energy sources are discussed. The chapter demonstrates that an operator should choose one or a combination of these three approaches based on its requirements.

2.1 Introduction

Renewable energy sources are being highly merged into the power systems. They can be found everywhere in different sizes either as a centralized huge power plant or as a distributed generation near the end-users [25]. Moreover, it is possible to apply several renewable sources as a hybrid system to meet the load requirements of a region [26].

In this case, combining these sources such as wind and solar with backup units provides more reliable, environment-friendly and economic load supply in comparison with a single source. There are stand-alone renewable sources which can be operated alone without the need of global network [27], [28]; however, stand-alone renewable sources are beyond the scope of this literature. The main target of this literature is an investigation of different aspects of emerging renewable energy sources in power systems.

Many kinds of literature have studied the impact of renewable sources penetration on voltage [29], frequency [30], [31], power quality [32], environment [32], power systems dynamic and stability [32], [33] and power losses [34]. Before analyzing renewable energy sources in power systems especially weather-dependent sources like wind and solar, their stochastic nature should be considered in order to increase the accuracy of the results.

The uncertainty of weather-dependent renewable sources has studied in some literature by different stochastic methods including possibility and probability approaches. Some literature used possibility approach which is divided into two categories including quantitative and qualitative methods [35].

The quantitative is used for epistemic uncertainty like fuzzy power flow analysis [36], [37], and the latter is for choosing the proper type of weather-dependent source for designers in planning stage [38]. In this survey, stochastic analysis of renewable energy resources in power systems operation is investigated through probability approach which includes Monte-Carlo simulation (MCS). Meanwhile, these uncertainties can be managed by some flexibilities like supply-side flexibility, e.g., capacity limits, ramping limits, minimum up/ down limits, energy storage availability, and transmission limit enhancement [39].

Moreover, [39] demonstrates the demand side flexibility for managing the sources uncertainties. In fact, renewable sources can be facilitated by demand response (DR) programs. Furthermore, impacts of stochastic nature of renewable energy sources on electricity market can be investigated for markets like day-ahead or balancing market because the market participants should make a decision in advance [39].

In fact, operators, due to their position, responsibility and duty, have to take proper measurements to address negative impacts of renewable sources uncertainties on the operation scheduling like total operation cost growth and deviations from scheduling. To this end, they have many options which one or a combination of some of them should be selected based on their requirements and capabilities. In this chapter, the most common, useful and modern strategies for operators are introduced and investigated through a comprehensive study among relative articles.

Some literatures like [40] studied uncertainty modelling techniques in power systems and its classification is for general usages in power systems. We study stochastic modelling techniques from weather-dependent renewable sources in different kinds of literatures which include stochastic dependency and independency, multi-dimensional dependence, forecast, and scenarios.

Afterwards, demand side management, which is one of the other approaches to deal with these uncertainties, is investigated and different demand response programs and some methods to model them are presented. Moreover, different methods of stochastic optimization in different market frameworks for dealing with uncertainties raised from stochastic renewable sources are discussed through relevant literature. This is a new classification of stochastic analysis of renewable resource among other works.

The chapter is structured in four sections. In Section 2.2, methods of dealing with the stochastic behaviour of stochastic generators including solar and wind are investigated. Applying demand side flexibility to confront power generation uncertainty is described in Section 2.3. Section 2.4 expresses the role of the electricity market to mitigate the effect of renewable energy sources uncertainty. Finally, in Section 2.5 conclusion and possible future work are presented.

2.2 Stochastic Analysis of Renewable Energy Sources

For obtaining enough information in terms of renewable sources output, forecasting their output is important especially for decision makers and operational problems. According to needs of operators, different methods are applied for tackling the renewable uncertainties; therefore, in this chapter from a deterministic forecast to a scenario-based one are studied.

In the following, various models for forecast and stochastic modelling in both dependent, independent, and the multi-dimensional state will be investigated which is demonstrated in Figure 2.1.

2.2.1 Stochastic Independency

Forecast and scenarios are in fact extrapolation. It means that a model is built and fitted to a set of data. The correlation between different stochastic variables may not consider, and the scenario generation or forecast is conducted, independently.

2.2.1.1 Point Forecasts

In this method, the renewable sources forecast are generated at time t for time $t + m$ which is m time after the time t and it is a single valued either. It means that having information at t the forecast value in $t + m$ is calculated. In other words, only one value will be generated in point forecasts method and this value can be used in both stochastic model and deterministic model.

In [41], point forecast of wind and solar are considered in both deterministic and stochastic approaches for comparison purposes in microgrid scheduling. In fact, the deterministic approach is a special case of stochastic approach with only one scenario. First, a day-ahead simulation is run through the forecast point of the wind and solar power output, and then, in real-time, the actual amount is replaced. The point forecast error will be compensated by energy storage systems in the microgrid.

2.2.1.2 Probabilistic Forecast

In contrast to point forecast, probabilistic one aims to get full information about what is going to occur in the future. It can be divided into some subsection.

2.2.1.2.1 Quantile Forecast

This method is based on quantile of the distribution function. It means, at time t a random variable is generated for time $t + m$, and then, a forecast of probability density function (PDF) or related cumulative distribution function (CDF) is issued to fit the random variable.

The random variables can be generated by different methods such as Markov chain Monte Carlo methods, pseudorandom generators, Metropolis-Hastings algorithm and so on. In quantile forecast, random variable in time $t + m$ determines a quantile which tells at time t there is a special probability (nominal level) that renewable energy generation will be less than its quantile at time $t + m$ [42], [43].

Moreover, it is in the form of threshold level related to probability and can be used for some operational problems. In [44], authors analyzed forecast error to build a model of quantiles of forecast error in wind farms. Wind power uncertainty was modelled in [45] through linear quantile regression by formulation a cubic B-splines for obtaining the quantile with a proportion of the forecast error.

Authors in [46] applied quantile forecast method for both solar and wind generator forecast which is used for deterministic power system unit commitment and comparison with the different probabilistic forecast method.

2.2.1.2.2 Forecast Interval

Quantile forecast method does not deliver any information about forecast uncertainty level. To this end, the forecast interval is used in [47]. Forecast interval is usually proper for robust optimization. Forecast interval has a nominal coverage rate and lower and upper bounds which define, for example, the probability that a wind farm generation is higher than a specific amount. Actually, forecast interval can cover point forecasts and quantile forecast through considering different nominal coverage rates. Therefore, full forecast distribution of stochastic variable like wind power can be obtained by this method [48].

2.2.1.2.3 Density Forecasts

Density forecast gives the whole information about renewable sources generation for the future. The produced PDF or CDF includes a complete description of the stochastic variable. In [49], to tackle wind power generation uncertainty, probability density forecasting provides an expected future values of uncertainties. To this end, a new type of forecast called weather ensemble forecasting is applied, which is generated from the atmospheric model and include several scenarios for the future value of a weather variable.

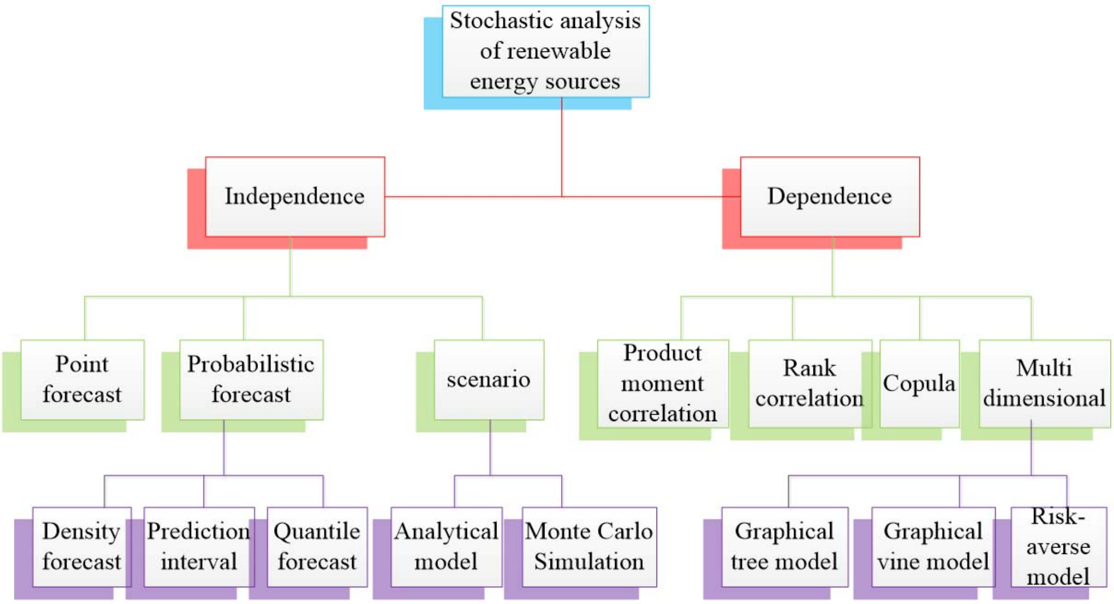


Figure 2.1 Various methods of stochastic analysis of renewable energy sources.

The distribution of these scenarios would be used as density forecast. Moreover, statistical time series techniques like daily wind speed or solar irradiance data of generalized autoregressive conditional Heteroskedasticity (GARCH) and long-memory time series model for a generation of density forecast is used [50], [51].

2.2.1.3 Scenario Forecast

In scenario generation method, some information about characteristics of the stochastic variable like renewable power generation is given. In a simple way, each lead time, location and renewable energy type are considered, independently. Since each forecast includes some kinds of errors and these errors can be in a relation with time and increase time by time, if the forecasts errors are not strongly correlated in time, the temporal dependence structure can be disregarded.

2.2.1.3.1 Analytical Methods

Analytical methods are based on convolution methods like fast Fourier transform method (FFTM), Multi-linear simulation method (MLSM) and point estimate method (PEM). In [52], FFTM is used for generation of a PDF for wind speed for some investigation about available transfer capability (ATC). MLSM is used in [53] for probabilistic load flow (PLF) of distribution system with the wind and photovoltaic (PV).

PEM is employed in [54], as a deterministic routine to find the statistical moments of output random variables. The article implements PEM to model the output power of solar and wind power generators. It is important to put some simplifications in their formulation. These simplifications are linearization, independence and normality. In linearization of the system model, the problem can be solved much easier because it permits the representation of the system outputs as a linear combination of systems inputs [35].

In independent assumption, system inputs are considered statistically independent. This assumption, in a combination of linearization, helps to compute outputs by series of convolution or application of Gram-Charlier expansion method and computation of cumulants of system outputs by system inputs based on their invariance to a linear transformation. This method is widely used for PLF [55]; however, some articles considered wind generators besides probabilistic load flow.

For example, in [56], authors used a combination of cumulants and Gram-Charlier expansion to calculate (PLF) containing large-scale wind power. In normality assumption, inputs are presumed to be normally distributed. This assumption let to apply linear correlation for the dependence structure among random variables [35]. Some literature mention that analytical methods need a fewer number of the simulation than Monte-Carlo simulation (MCS) method [57].

2.2.1.3.2 Monte-Carlo Simulation

MCS methods are the most accurate and straight-forward method; however, it needs remarkable computational efforts [57]. For the wind or PV generation, a PDF should be assigned for every time period. In the most articles, Weibull PDF is considered as the best function for modelling the stochastic behaviour of wind power generation [58]–[61]. Beta PDF is generally dedicated for the stochastic attitude of solar power generation [62], [63].

With determining the proper PDF, related PDF for every time period is generated through the expected or forecasted value of the wind or solar power generation. A large number of scenarios can be generated by fitting random variables to the PDFs with equal probability. The procedure is repeated for a number of iterations.

Some methods like Latin hypercube sampling (LHS) [64], sample-splitting approach (SPA) [65] and fission and roulette(F&R) method [66], are used to decrease the computation burden of MCS. Therefore, in each scenario, there are t time period (based on the horizon time) random wind or PV generation based on forecasted generation [67].

2.2.2 Stochastic Dependence

Some simplifications like independency between random variables and considering all PDF as Normal distribution would not get the accurate results and are full of fallacies. Therefore, it is essential to consider stochastic dependence between system inputs especially from output aggregation of multiple renewable generation inputs. The difference dependence structures yield different distributions around the same central point [35]. In this sense, it is required to find a way to measure the dependence between random variables.

In [35], this correlation between two stochastic power generators is considered. The most common method is the product moment correlation (PMC) or linear/Pearson correlation which for the dual case is as follows:

$$\rho(X,Y)=\frac{E(XY)-E(X)\times E(Y)}{\sigma(X)\times\sigma(X)}=\frac{E[(X-\mu(X))\times(Y-\mu(Y))]}{\sigma(X)\times\sigma(X)}=\frac{Cov(X,Y)}{\sigma(X)\times\sigma(X)} \quad (2.1)$$

where X , and Y are random variables with finite expectations of $E(X)$, and $E(Y)$, finite variance $\sigma^2(X)$, and $\sigma^2(Y)$. If there are N pairs of samples from variables, it calculates the population product moment correlation as follows:

$$\rho_{x,y}=\frac{\sum_{i=1}^{N}(x_i-\overline{X})\times(y_i-\overline{Y})}{\sqrt{\sum_{i=1}^{N}(x_i-\overline{X})^2}\times\sqrt{\sum_{i=1}^{N}(y_i-\overline{Y})^2}} \quad (2.2)$$

where:

$$\overline{X}=\frac{1}{N}\times\sum_{i=1}^{N}(x_i) \quad (2.3)$$

$$\overline{Y}=\frac{1}{N}\times\sum_{i=1}^{N}(y_i) \quad (2.4)$$

Some of the results of equations (2.2), (2.3), (2.4) in some particular condition are as follows:

- If X, Y are independent, then: $\rho(X,Y)=0$
- If X, Y are linear dependent, i.e., $X=aY+b$, then: $\rho(X,Y)=1$.

If the problem is not in the normal domain just in linear condition, it provides completely stochastic dependence; however, in non-linear states, it may cause some misleading. In other words, for two wind power generation, it cannot be introduced linearly because the distribution function is Weibull and the distribution is not linear. Therefore, it leads to introduce rank correlation [68].

In rank correlation, instead of measuring the correlation between the real amounts of random variables, the samples are ranked from lowest to highest, and then, the product moment correlation for responsive ranks is measured. In other words, the value of each sample is replaced by the value of its rank among other samples and product moment correlation is calculated using the ranks.

By using CDF to random variables, marginal distributions are transformed to rank. For example, authors in [69] transferred random variables of wind speeds, solar irradiance to a rank domain by using CDF transformation and stochastic dependence was examined. Moreover, for considering multivariate stochastic dependence, diagonal band copula, which will introduce later in this part, was applied.

In fact, through this method, dependence structure from marginal is decoupled, and the information of dependency between random variables is maintained in these ranks. Moreover, for multivariate distribution function Copulas are a function to couple them to their single dimensional margins [70]–[72].

As can be seen in Figure 2.2, it has different types including Sklar's theorem [73], Frechet-Hoeffding bounds, Gaussian Copulas, Normal Copula, Elliptical Copulas, Archimedean Copulas and Diagonal band Copula [69]. In [74], an integration of PV and wind turbines in a distribution network were studied using Archimedean copulas.

2.2.3 Multidimensional Dependence

Multidimensional dependence model has to be modelled based on available information. In this sense, joint normal transform (JNT) is suitable for a stochastic system with adequate information [75], which is an extension model of the normal copula. According to this model system correlation matrix is build.

Therefore, in multidimensional dependence method, the matrix should be semi-definite, which without it, it can be a problem for this method. To solve this problem, it is required to fill the matrix with positive semi-definiteness amounts and convert the matrix into a consistent one. In the case of lack of enough information and increasing the uncertainty or dimension, some methods like graphical model trees and vines [70] should be applied based on available information.

Another way for modelling high-dimensional Gaussian distributions is to simplify the multidimensional dependency model by a risk-averse model reduction technique [76]–[78]. It means that instead of making dependence between all random variables, risk-averse model is divided into groups which are called stochastic plants.

In Table 2.1, a summation of different mentioned methods for modelling stochastic nature of weather-dependent renewables in different articles are classified based on publication year. As can be seen, due to the accuracy of MCS and also since MCS gives more completed information about stochastic behaviour of the variables, the trend of using MCS is being boosted.

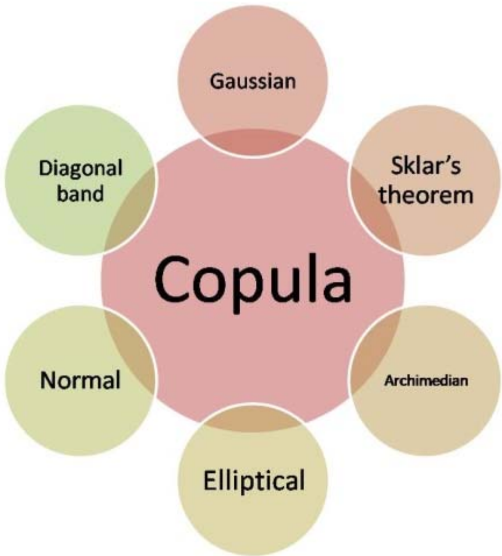


Figure 2.2 Different types of Copula methods.

Table 2.1 Taxonomy of different methods for modelling renewables uncertainties.

Year	Point Forecast	Quantile Forecast	Forecast Interval	Density Forecast	Scenario Forecast (Analytical Methods)			Monte-Carlo Simulation		Product Moment Correlation	Rank Correlation	Copula	Multi-Dimensional Dependency
					FFTM	MLSM	PEM	Wind	Solar				
2016								[40]	[40]				[76]
2015		[46]			[52]			[61] [63]	[62] [63]			[69]	[75]
2014	[41]					[53]							[77]
2013			[47]										
2012				[50]			[54]					[73]	
2011		[45]											[78]
2010			[48]									[74]	
2009				[49] [51]				[58]					[70]
2008		[43]						[59]					
2007										[35]			
2006		[44]									[68]		

2.3 Uncertainty Tackling by Demand Side Flexibility

Demand side can participate to system flexibility to confront uncertainties raised from weather-dependent renewable sources. To this end, some measurements can be taken like shifting energy from high demand to low demand periods and lowering peak demand [39]. Growing of the communication facilities, advanced metering infrastructure (AMI) and internet-of-things (IoT), the potential of using demand flexibility integrated by renewable energy sources is going to be higher [79], [80].

The advantages of using DR include the ability to balance fluctuations in renewable generation, facilitate higher penetration of renewable sources on power systems, an increase in economic efficiency through the implementation of real-time pricing, and a reduction in generation capacity requirement, which are studied in [81].

However, there are some challenges faced DR including lack of experience and consequently need to employ huge assumption for modelling and evaluation sources. If a DR program is implemented successfully, an acceptable effect of DR in electricity price reduction can be revealed [82]. The existence of renewable energy sources can cause a reduction in electricity prices especially when wind production comes as an extra production to the system with zero marginal price and when there is a high CO_2 tax for thermal generators in the market [83], [84].

Therefore, one of the other advantages of DR In these conditions and in pricing area is hedging cost reduction. As it will discuss in the next part, DR program has different types of implementation which according to the proposed usage can be applied, properly.

For compensation, the shortage power of weather-dependent renewable sources due to their inaccurate forecast, one of the DR programs is applied. One approach is providing direct control of customer; however, it is less acceptable for customers. According to [85], one of the best ways to get customers flexible is running a real-time pricing of electricity. It means that price-based elastic and load-shifting responses should be made. Moreover, authors have mentioned that using price-based elastic during low-wind events, peak demand in the UK may be reduced, significantly.

2.3.1 Various Demand Response Modelling

In this section, first the regular classification of DR programs is introduced, and then, some assumptions and models implemented by the literature in smart grids are discussed.

2.3.1.1 Demand Response Programs

There are some different DR programs which regarding the special utilization can be applied. Literature has classified DR programs in different ways; however, the most suitable and common ones are described in [13], [80], [86]–[88] where DR programs were classified into two categories including dispatchable and non-dispatchable, as can be seen in Figure 2.3.

In dispatchable DR programs, customers participate voluntarily in a special scheme for controlling customers appliances by operators [89]. For example, the operator can directly control the appliances like air conditioners during peak periods. Two methods in this category, including direct load control (DLC) and interruptible/curtailable service (I/C), are being used since long time ago [80].

In these aforementioned methods, operators make an incentive for reducing or curtailing the consumption of customer who has either contract (I/C method) or no contract (DLC) [87]. In emergency DR program (EDRP), customers need to respond only during the emergency period of time and operator pay customers in those time period. In the capacity market program (CMP), some customers offer a specific amount of load reduction in advance when the grid is in needs [88].

In demand bidding (DB) method, customers bid amount of load reduction in the wholesale market. In other words, customers identify how much load would like to curtail at a posted prices [86]. An ancillary service DR works as a reserve source. The customer can bid load curtailment in Independent System Operator (ISO) as an operating reserve, and if accepted, ISO pays customers for committing to be standby. In case that costumers capacity is needed, ISO calls them with spot market price [86].

Calling demand response even in spot price has economic justification for ISOs why total operation cost will be dropped due to the fact that no forced load curtailment, which is much more costly, will be occurred and there will be less need to occupy generators capacity as reserve. Although ISO will pay for DR with spot market price, it will provide convenient for customers and increase the network reliability. Moreover, DR implementation will prevent to construct new power plants to supply loads.

Non-dispatchable DR programs, which can be called price-based programs, are based on dynamic pricing rates which their main intention is shaving demand profile. One of such methods is the critical peak pricing (CPP) which generally is implemented in contingencies with real-time prices [90]. Another one is the real time pricing (RTP) where participants are informed about prices on day-ahead [91]. In other words, the prices change continuously during the day. In time-of-use (ToU) method, two or more daily periods are established to show peak hours and off-peak hours to charge a higher rate during peak hours [86].

Table 2.2 demonstrates a classification of different DR programs and the literatures that have employed each one along with the certain contribution which the literature has been offered for the specific DR program.

2.3.1.2 Demand Response Conditions

For the implementation of DR programs, due to lack of enough experience, some assumptions should be considered in modelling approaches. Therefore, advantages of DR models highly depend on these assumptions and it needs to be evaluated yet. Some models and assumption are introduced in the following sub-sections.

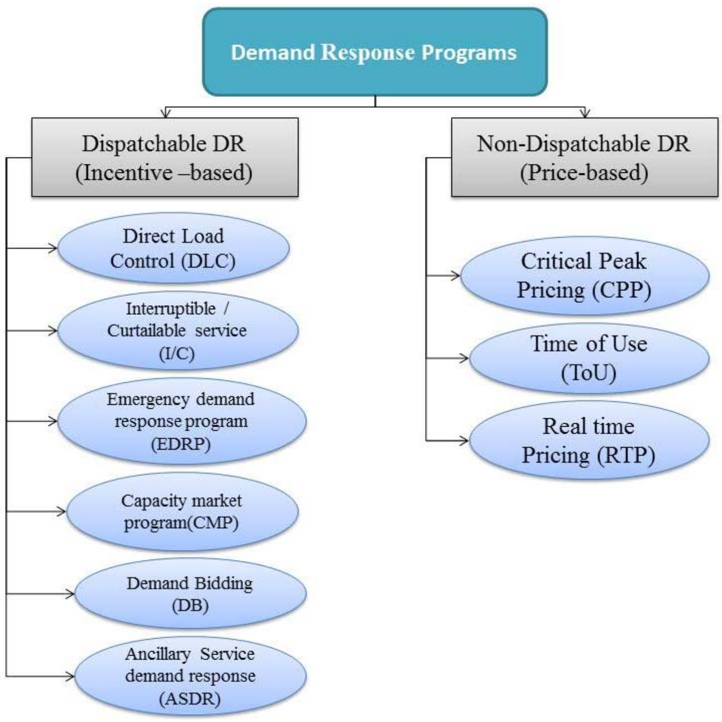


Figure 2.3 Demand response programs categories.

Table 2.2 Taxonomy of Different DR programs.

Reference	Demand Response Programs								Contribution
	DLC	I/C	EDRP	CMP	ASDR	CPP	ToU	RTP	
[92]	√		√						Distributed DLC for large-scale residential DR by two-layer communication-based control
[93]		√		√					Modelling by price elasticity of demand and customer benefit function with considering penalty for consumers
[94]	√					√			A new linear mathematical model for implementation an emission-based UC program
[95]			√						With considering dynamic elasticity factor, price responsiveness is realized
[96]								√	Optimizing the negotiation among customers and retailers through considering power-purchase of customers energy in an RTP DR
[97]					√				Competitive transactions among expensive spinning reserve of thermal units and demand side reserve source for satisfying power balance constraints
[98]							√		Defining the optimum ToU tariff rates in face of high penetration of Renewables to encourage customers for participation in ToU program.

2.3.1.2.1 Demand Behaviour

It is expected that demand behaves in a rational way especially economically. To this end, it is common to consider a value as an elasticity of demand which is selected at random with a few considerations for the physical features and limitation of demands. In order to model the load behaviour with more precision, instead of considering the single elasticity value, which can only reflect the increase or decrease of consumption, the usage of an elasticity matrix to incorporate both self and cross-elasticity [99] is desired. Cross-elasticity is for shifting demand to another time because of change in prices at that time.

For example, the author in [100] considers the wind generation in a period of time less than what was expected, and the prices get higher. Therefore, demand responds to the higher prices at that time (self-elasticity) and the shifts to the lower prices time period (cross-elasticity).

2.3.1.2.2 Negative Supplier

Another modelling approach is merging DR into unit-commitment. Individual loads can be aggregated to consider as some large units to participate in the market. In this approach, DR is modelled to negative generation with minimum and maximum consumption constraints and ramp rate limitations. The load can be reduced or shed according to the uncertainties in the network based on unit commitment decision. For example in [101], authors showed the DR as a reserve in two-stage stochastic unit commitment in order to confront, somehow, the uncertainties in microgrids like wind and solar power generation. In this model, DR bidding is divided into several levels and stepwise related price.

In [6], DR has been scheduled as ancillary service in a power network by considering contingencies in a two-stage stochastic programming. However, the DR bidding curve is like a supplier price curve (e.g., Figure 2.4) because it is treating as a negative supplier, and when more demand is chosen in this program, more will the cost prices.

In fact, when demand response is assumed as a supplier commodity, a supply curve for demand response price would be required. In other words, the more load quantity is considered for demand response, the higher price should be paid by operator to customer. For example, in some programs like load curtailment, load shifting as well as ancillary service demand response are like the Figure 2.4.

2.3.1.2.3 Demand Bidding

Load demand can participate in the market, actively through price bidding. In other words, loaders bid their desired prices in the market. To this end, some of the loaders are considered as fixed loads which are price-takers and would be settled in market-clearing price. Moreover, other loaders are considered as flexible loads which can be dispatched based on the responsive load-prices which would decrease with increasing the load quantity (such as Figure 2.5).

In other words, since in this model the customers offer their consumption, a demand curve like in Figure 2.5 for price bidding would be required. It means, the more load quantity is demanded for consumption by customer, the fewer prices will be allocated for that quantity. Therefore, after ISO's decision about customers bidding, some loads are scheduled and others not which means a volume of loads would not be served as a DR program.

This is considered as flexibility of demand side and a potential of making balance between demand and supply in power system operation. Accordingly, flexible loads are subject to several constraints including, minimum up/down time limits, load ramp up/down rate, allowable bound of curtailment, either hourly or daily [102].

Minimum up-time denotes the successive hours that a load must be supplied while restoring. Minimum down-time defines the sequential number of hours that a load would be shed after curtailing process. Load ramp-up represents the load ramping capability of restoring and load ramp-down implies the load ramping ability to curtail. In fact, this rate reflects the consumption change of flexible loads [103].

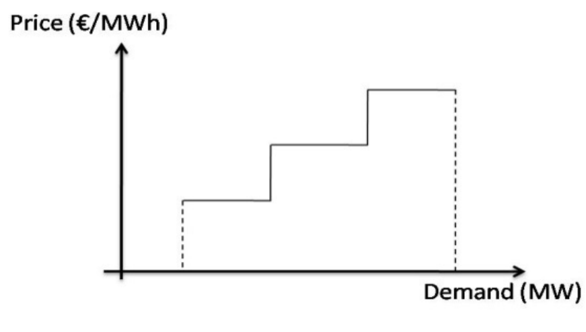


Figure 2.4 Demand response bid curve as negative supplier.

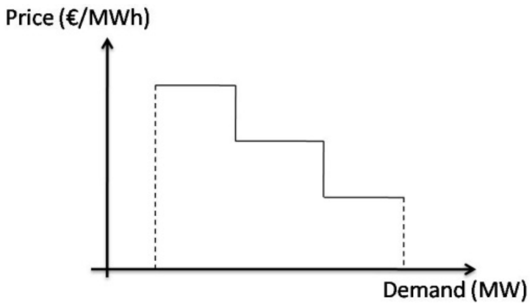


Figure 2.5 Demand response bid curve for demand bidding.

Allowable bound for load curtailment divides into two parts: minimum hourly curtailment and maximum daily curtailment [104]. The minimum hourly load curtailment can be caused by physical load limitation or system operator where the lower load cannot participate in the market as a responsive load. Maximum daily curtailment denotes a reasonable restriction for total curtail in the time horizon [105].

2.3.1.2.4 Demand Response Aggregation

In order to help customers to qualify their forecasts for DR programs, some entities are introduced as DR aggregator, which are independent of the system operator. DR aggregator can be a distribution system operator, a load serving entity or a financial entity [106]. In the model of [106], DR aggregators are in contact with system operator and customers to perform a better DRP [107].

DR aggregators are responsible for receiving the customers' bids for DR and sending it to wholesale electricity market [108]. To this end, DR aggregators evaluate the customers' potential to dedicate the special DR quantity and price based on physical or operational constraints. Moreover, to decline the number of DR contracts, aggregators gather similar customers in terms of DR strategy and prices.

There are some different physical load reduction strategies including load curtailment (LC), load shifting (LS) and load recovery (LRC) which can be performed by DR aggregators [109]. In LC, customers decline their load and do not shift their consumption to another period of time, by turning off the television, lights, computers or air conditioners without any alternative time for consumption.

In LS, a load reduction and shifting consumption to other time period are performed. In LRC, the process is the same of LS, but the exact alternative time for consumption is defined. In LS strategy, the shifted consumption can be whenever is required [110].

2.3.1.2.5 Demand Response Price Modelling

In cooperation of demand and retailers, most of the times, retailers present a fixed price to customers to participate in a DR program which does not include any incentive for the customer to modify their consumption [106]. In order to provide more flexible loads, demands can be controlled through price signals.

The ToU pricing is an alternative approach to get rid of fixed-price tariffs. This scheme, which has been already applying in different countries, not only the electricity prices are higher during peak hours than off-peak hours, but also some incentives are made for consumption during night hours rather than day hours by lower prices [39].

In [111], a ToU approach has been scheduled by particle swarm optimization (PSO) for manufacturing customers in the presence of renewables, and the effect of ToU pricing profile is studied.

Authors of [112], and [86] provided a framework for implementation of ToU according to load elasticity concept. ToU program is a static pricing scheme. It means that prices for peak hours, off-peak and valley times are fixed for a long time. Hence, it is not able to follow renewable sources fluctuation.

Real-time dynamic pricing is used to adapt a rapid variation of renewables, which in higher renewable production hours leads to lower market price, and vice versa [113]. These methods need to apply faster and simple response because it should be conducted near to real-time frameworks. Therefore, some pre-defined requirement should be addressed including:

- Bidirectional communication infrastructure to send and receive data like consumption state and price signal;
- Intelligent appliances to schedule the optimum consumption based on the price signal and sending pre-defined consumption to entities for adjusting the price;
- Simple controlling and optimization solvers to get the results near to real-time.

In [114], authors has proposed a model to maximize customer utility or minimizing energy cost of a household or a small business through their energy management system (EMS). In fact, based on real-time pricing scheme, an optimization model has been provided to adjust hourly load level into hourly electricity price.

Optimal real-time prices have been obtained by a few message exchanges over a communication network in [115]. To this end, a two-stage problem has been solved to maximize the quality of consumption and minimize electricity bill from user's point-of-view and maximize the profit from retailer's viewpoint.

Authors in [116] have proposed a control scheme for adjusting set-points of some high consumption appliances in households according to real-time electricity retail price and threshold price that customers set to minimize the bill. Real-time retailing-prices releases every 15 minutes and the accordingly load can be shifted from peak-hours.

Moreover, in [117] was presented a locational real-time tariff scheme to cope with time and location variability of renewables which cannot be reflected through residential tariff scheme. Real-time pricing for industrial customers, to grow the proportion of wind power generation, has been performed in [118]. The real-time pricing tariff for customers includes half-hourly wholesale market, price and fixed supplier mark-up, which largely consists of system marginal price.

Likewise, an optimization approach for obtaining real-time prices, on behalf of DR aggregator has been presented by [119], where DR aggregator serves deferrable loads by renewables, and in the case of any shortage, it can decide whether to curtail the load or procure from the wholesale based on dynamic real-time price scheduling.

2.4 Electricity Market Role for Mitigation of the Stochastic Nature of RESs

In the electric power industry, there are two methods of trading electricity. On one hand, the first one is long-term trading which is a bilateral contract and performs through future markets. On the other hand, the second one is short-term trading which is an electricity pool. This market structure is demonstrated in Figure 2.6. In bilateral contracts, a buyer and a seller make a forward contract that involves the trading of a specified amount of energy. Essentially, bilateral contracts are agreements between two parts outside the organized market [120].

Regarding the electricity pool, it can be divided in two trading arrangements, day-ahead market, intraday market and balancing market. They are operated in a similar way, as described later; however, the difference is in time of which they take place. The day-ahead market takes place one day before the delivery of energy, the intraday market is scheduled some hours before energy delivery, and the balancing market takes place a few minutes before the energy delivery. So, the electricity pool allows short-term trading and consists of by several buyers and sellers which are market participants.

The market is cleared by a market operator, generally in an auction. Basically, the producers present their offers and consumers submit their consumption bids. Then, the system operator combines these offers and bids to construct aggregate curves of supply and demand. The intersection of these curves corresponds to the market clearing price. Therefore, those suppliers who have submitted their offers below market clearing price and the consumers who have submitted their consumption bids above market clearing price are scheduled [121].

The increase of renewable energy sources (RES) in today's markets has caused some problems that can be solved through the markets structures. Due to meteorological origins of stochastic RES, all of those sources are influenced by the weather. The wind generation depends largely on wind speed and less on air density; moreover, irradiance and temperature influence on the solar production. This meteorological influence on the generation of renewable sources makes this production uncertain and hard to predict [121].

In contrast to conventional units, production of RES is characterized by non-dispatchability, and for this reason, forecasts are needed in order to schedule the units. In addition, RES has priority over conventional units why its marginal cost is low. Due to the high penetration of RES allied to deregulation of the electricity industry and for increasing the system reliability, a transition from traditional deterministic approaches to stochastic approaches is being widely performed.

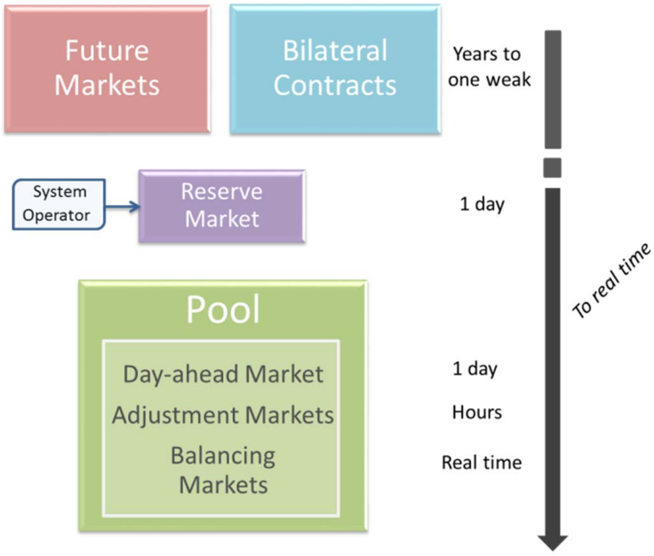


Figure 2.6 Market Structures.

Deterministic problems can only be used when the situation for the next day is definite. Stochastic programming models are capable of determining the energy and reserve dispatch for the day-ahead market. These models are capable of handling renewable sources, demand variations and the failures of power system components.

Thus, stochastic production is normally dispatched in a point forecast of its output distribution. These approaches use optimization models, such as Unit Commitment (UC) to facilitate the decision-making process of scheduling and dispatching electric power generation resources [122], [123].

To guarantee UC solutions, some requirements such as security, reliability and reverse along with their constraints should be taken into account [122]. In this context, some of the potential market solutions for RES variation are analysed for the day-ahead market, intraday market, balancing market, and demand response exchange market (DRX).

The DRX is a relatively new and separate market for trading demand response in a deregulated power system which is a powerful mean to cope with problems raised from renewables uncertainty.

2.4.1 Day-Ahead Market

The day-ahead market takes place one day before the energy delivery, usually close to noon. In this market, one of the important commodities which are traded is a reserve that guarantees the balance at any time. System operator needs a reserve to cope with uncertainties in power systems.

Some approaches are presented later to show how RES can be integrated into the market industry [124]: two-stage[125], chance-constrained [126], a combination of two-stage and chance constrained [67], multi-stage [127], [128] and robust programming [123].

2.4.1.1 Two-Stage

In a two-stage approach, decisions can be made in two different categories, day-ahead market and real-time decisions. According to references like [129], a stochastic security constrained unit commitment (SCUC) model has been presented to clear the energy and reserve market considering the uncertainty of renewables and/or loads, contingencies. High penetration of wind generators brings new challenges to the system operator and may increase the operational costs.

The main objective of this approach is to minimize these costs. This approach consists of two parts; the first part is related to the decisions made in the day-ahead market, such as the cost of start-up, shut-down, generation, and spinning reserve. The second part represents the real-time costs of activating the reserve, wind curtailment and shedding loads. It is also considered the uncertainty of wind production through wind scenarios [130].

Reference [125] is an example of a two-stage approach to facilitate wind integration through network reconfiguration. In some papers like [125] and [131], benders decomposition is employed to decompose the problem into two parts due to a high number of variables as a consequence of scenarios and line status [132]. Therefore, dispatch in real time should be carried out to minimize operational costs.

Reference [133] has applied hourly forecast errors of wind energy and loads to schedule the optimal reserve. In fact, a stochastic two-stage programming for solving an SCUC and getting the scheduling of wind energy along with conventional units with N-1 contingencies. In addition to the method used in the previous paper, value at risk has been put in [134] to consider wind power forecasting error.

2.4.1.2 Chance Constrained

There is another method to solve stochastic day-ahead scheduling problem in electricity markets is introduced for satisfying the stochastic and the reliability criteria in power systems.

This approach is based on chance constrained, and it considers random outages of system components and the errors originating from renewable sources and load variations. To accommodate these errors from renewable sources, enough spinning reserve should be considered in the day-ahead scheduling.

The proposed model follows some topics: for more accuracy in forecasting, renewable energy would be dispatchable in real time markets. In the case of a contingency, the system security would be jeopardized if the system is not able to change rapidly to a stationary state.

The chance constraints in [126] are the hourly reserve requirements and line constraints. These constraints can be converted to deterministic equivalents, and a standard solution technique is applied. The renewable generation forecast error is presented as a normal distribution.

Briefly, the major steps of the method are:

- **Step 1**: Identification and elimination of inactive line flow constraints for the case base and contingencies;
- **Step 2**: Solution of master UC problem solved by a mix integer linear programming (MILP) based method. The master UC problem is divided in hourly UC and economic dispatch (ED);
- **Step 3**: Base case evaluation, where the network security evaluation for the base case is performed by the ED obtained from step 2. If some line violation occurs, the network security evaluation is run. The step 2 and 3 are repeated until there is no violation in the base case;
- **Step 4**: Contingency evaluation, it is calculated the hourly maximum flow for each line in each contingency, after obtaining the UC in case 3. The steps 2, 3 and 4 are repeated until there is no more violation in base case and contingencies.

The authors in [67] present another method to deal with wind power forecasting errors for keeping the reliability of the system in case of any fluctuations in wind power output. This method is mostly for taking the most advantage of wind power. Therefore, they merge two-stage programming with chance-constrained to solve a UC in an uncertainty environment.

Chance constrained is applied to formulate the problem in order to guarantee that a significant part of wind power will be used in each hour. The first stage of the two-stage approach is related to traditional unit commitment problem with transmission constraints, and the total amount of wind power should be delivered.

In turn, the second stage represents the penalty cost due to wind power. As the wind power usage was guaranteed by the chance constrained, if wind power output is higher than scheduled wind power, the excess can be curtailed without penalty. In contrast, if the wind power output is lower than the scheduled one, penalization for the shortage of energy will occur. Therefore, this model can help to increase the usage of wind power and the chance constrained allows guaranteeing a maximum usage of wind power with the lowest possible curtailment.

2.4.1.3 Robust Programming

Robust Programming represents another solution to deal with uncertainty, but unlike stochastic approaches, this method does not require scenarios. In addition, contrary to stochastic programming where minimizes the total expected cost, in robust programming the minimization of the worst-case cost regarding all possible outcomes is expected [122].

Robust approaches have been studied considering uncertainties such as wind power [128], wind power with demand response [105] and also wind power with pumped storage hydro [135]. In [123], a problem to determinate the day-ahead market dispatch in an electricity market is developed with considering stochastic generation sources. A robust optimization model is presented to minimize the system cost for the worst case realization of the uncertain production. In this case, the uncertainty is represented by sets of polyhedral prevenient from historical data.

The major steps of this approach are briefly presented:

- **Step 1:** To determinate the day-ahead energy and reserve dispatch a robust optimization is applied. The system operator finds the amount of required reserve and the optimal dispatch for the day-ahead market;
- **Step 2:** It is proposed a reformulation of the inner max-min problem to determine the uncertainty and alternative solutions which can adjust polyhedral sets for a precise solution. The max-min determines the worst case realization through maximization problem, and the recourses cost is minimized in the minimization problem;
- **Step 3:** The results from robust approach are compared to deterministic and stochastic programming.

2.4.1.4 Multi-Stage

Multi-stage models deal with the uncertainty in several time framework or horizon time. In other words, this would be considered as the extension of two-stage approach which just the uncertainty of one time framework is taken into account. Hence, multi-stage models capture the dynamics of uncertainties over time, and the decisions can be adjusted dynamically [136], [137]. In some papers such as [122], [138], scenario trees are used to facilitate the formulation of this kind of models. In these approaches, the information can be updated hourly or multi-hourly and facilitate the decisions-maker's adjustments according to current states of the system and future uncertainties. Therefore, the relation between decisions making and the uncertainties becomes closer and precise. Reference [139] presents a dynamic multi-stage model to operate isolated hybrid wind-diesel power system. A dynamic programming has been applied to deal with future uncertainties in the system.

2.4.2 Intraday Market (Adjustment Market)

Weather forecast always includes errors and uncertainties. In fact, the closer we are in target hour, the more precise weather forecast we have. Through this concept, the intraday market has been introduced between day-ahead and real-time [140]. Since it is closer to real-time, revising the operation decisions with updated weather data would be applicable which helps to mitigate the uncertainty of the wind and solar power [141], [142].

The intraday market is shorter than day-ahead and can be divided into several sections i.e. two, three or more for each day. Some literature has investigated the benefits of the intraday market to mitigate the weather-dependent renewable sources. Authors in [143] assessed the benefits of the intraday market compared with the day-ahead market in a competitive environment based on some criteria such as expected reserve, expected load shedding and expected wind power spillage.

According to their methodology, at the end of each intraday gate closure, the program is cleared and rerun by updated forecast information. Each rerun provides operation schedules and prices for remaining hours of horizon time which are binding for the very next intraday market and non-binding for other remaining intraday markets.

Outputs of this intraday market are energy, reserve and price for the very next intraday market and expected energy, expected reserve and expected price for other next intraday markets. In [144], authors believe that intraday market is a more expensive method to balance forecast errors than the day-ahead market due to the shorter response time. However, balancing market is on average more expensive one, so the intraday market is more acceptable.

2.4.3 Balancing Market

The balancing market corresponds to the last minute energy adjustments. A non-dispatchable producer has to participate in this market to cover the deviations from the production pattern settled in the pool. In this market, it is ensured that the balance between generation and demand is settled through corrections of energy imbalances. These imbalances can be positive or negative. A positive deviation occurs when the production is higher or the consumption is lower than scheduling. A negative deviation happens, when the production is lower or consumption is higher than scheduling. Consequently, the producers must sell the excess energy or buy deficit energy based on imbalance price. For obtaining prices of selling and buying an auction is made.

In the case of a positive imbalance (excess of energy), producers only repurchase their excess in a price lower than the day-ahead clearing price. So, the market participants who sold their energy in balancing market obtain a profit lower than if they sold all their production on the day-ahead market. In contrast, if the system imbalance is negative (deficit of generation), required energy will be at a price higher than the day-ahead market. Balancing market should be considered as the last mechanism to provide energy balance [121].

In [125], in order to show the impact of wind uncertainty on real-time scheduling, three different cases were studied. In the first case, the real time wind production is equal to the expected value. Therefore, it is not necessary to have a spinning reserve or loads shedding; therefore; what is scheduled in the day-ahead market is still the same in real time. In the second case, the expected value is higher than the real-time wind generation. Here, to cover the excessive amount of wind generation it is necessary to allocate down-spinning reserve.

To decrease the power flow in lines, load shedding and wind curtailment are two possible solutions. Since load shedding is the most expensive option, wind curtailment is chosen. The third case is when wind generation is lower than the expected value. Consequently, the up-spinning reserve is required and other solutions such as load shedding or bringing new units online should be considered. As assumed earlier, load shedding is an expensive solution, so the second option is the most economic.

In [145], microgrid aggregator concept has been introduced in a balancing market bidding to depress the effect of RES uncertainty. All in all, the operation costs are higher in the third case. A summary expression of the above three markets is demonstrated in Figure 2.7.

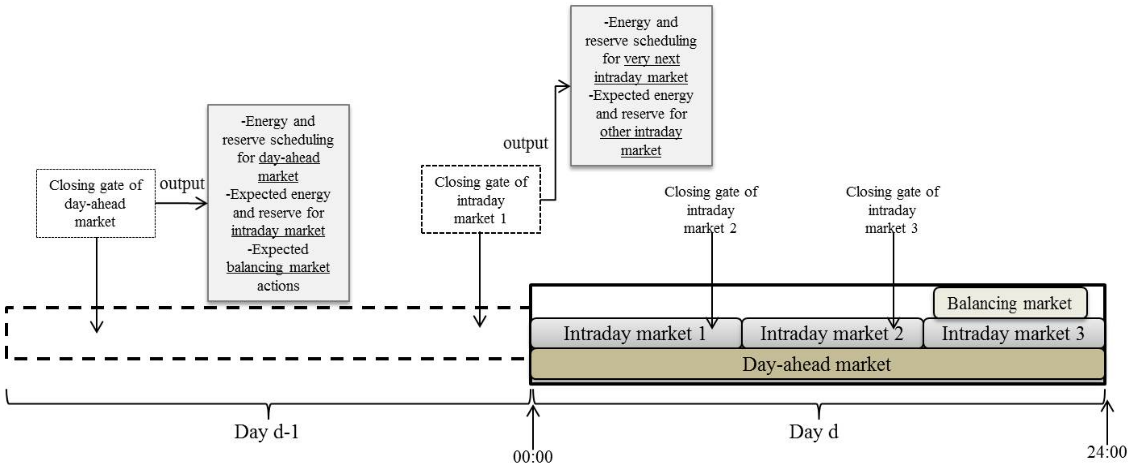


Figure 2.7 The framework of short-term electricity market.

2.4.4 Demand Response Exchange (DRX) Market

In the DRX concept, DR is treated as a market with an exchange among buyers including transmission companies (Transcos), distribution companies (Discos) and retailers and sellers including energy service companies (ESCos) [146]. The ESCos include load serving entities (LSEs), Distribution system operators (DSOs) and Demand response providers (DRPs). The structure of DRX market is demonstrated in Figure 2.8.

Buyers target for participating in DRX is to provide security and reliability for their network. ESCos as Sellers are responsible for registering, aggregating, scheduling, managing and clearing the DR. They do not have the capability for controlling and commanding to customers and manipulating retail prices like retailers; however, both of them are dealing with customers.

Supplying DR is performed by reducing the customer consumption. Therefore, in addition to the above key participants in this market, customers are other participants as DR producers [147]. DRX includes competition in a way that sellers lose the opportunity when they propose a payment far above true cost. Similarly, when buyers want to pay less than true price of DR, they cannot purchase this DR that is better to allocate other buyers who want to pay enough for this DR [146], [148].

There are two models for the DRX including bilateral and pool-based. In the bilateral model, DR exchange is directly carried out among sellers and buyers for a specific price and amount of DR. Although a regulatory like DRX operator (DRXO) follows the contract whether they obey the market policies. In the pool-based model, a central market is introduced for settlement and coordination by DRXO. In fact, the DR capacity is collected by DRXO in a framework which all sellers and buyers have to access this framework [146], [148], [149].

In [150], authors proposed a pool-based DRX model for managing the renewables variability. In this model, DRX is inside the stochastic day-ahead market run by ISO. In this procedure, first, a stochastic day-ahead scheduling is performed with considering forecast errors of renewable renewables and other uncertainties like random outages of components.

Applying the output of day-ahead scheduling which is the expected locational marginal price (LMPs), the DRX is run and cleared successively. In Table 2.3 a classification of reviewed literatures related to electricity market is presented. Accordingly, different literatures are categorized based on the utilized markets.

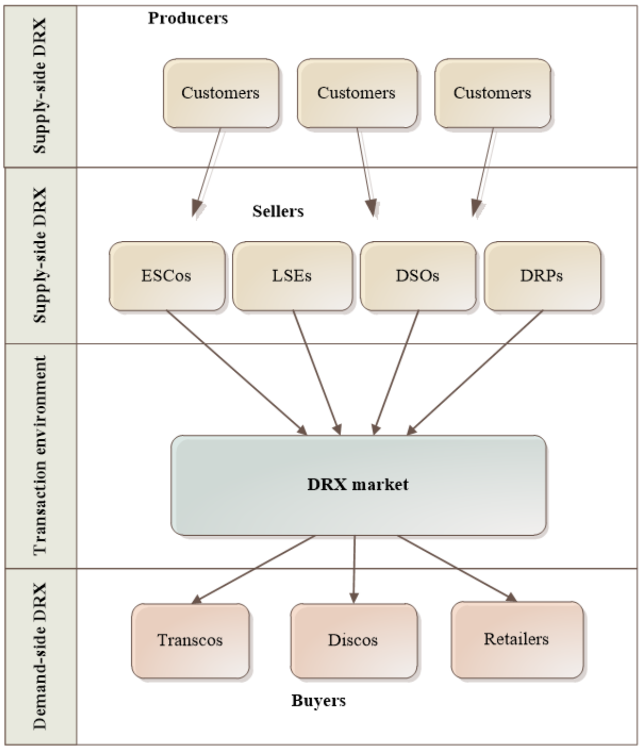


Figure 2.8 DRX market framework.

Table 2.3 Taxonomy of different markets and relevant literatures.

Reference	Day-Ahead Market				Intraday Market	Balancing Market	DRX Market
	Two-Stage	Multistage	Robust Programming	Chance Constrained			
[150]	√						√
[125]	√					√	
[145]					√	√	
[143]		√			√	√	
[139]		√					
[123]			√				
[67]	√			√			
[130]	√					√	

2.5 Brief Remarks from the Survey

In this chapter, some different approaches to tackling the stochastic nature of renewable energy sources, especially weather-dependent ones, have been investigated. Mathematical methods for forecasting scenarios in both dependent mode and independent mode were studied. Moreover, since another efficient approach to confront renewable sources uncertainty is demand side management, different kinds of DR programs and some modelling methods have been studied in this chapter.

In addition, by the liberalization of the electricity market, it is possible to cope with the problems raised from the inherent stochastic features of the wind and solar generators. The role of various market schemes and optimization approaches to optimize reserve for mitigation of these uncertainties has been studied.

Accordingly, there are many methods for the operator to cope with the uncertainty of weather-dependent renewables. Therefore, the operator can schedule the supplied energy more precisely and with less total cost. The outputs of the analytical methods have been employed by the operator either in one of the market schemes or in one of the DRPs.

Multidimensional dependency model enables the operator to deal with several stochastic variables like wind generators and solar generators, simultaneously and in a dynamic method, which leads to accurate results. Therefore, studying and applying this model more than ever can be caused to solve some restrictions related to modelling uncertainties in energy scheduling.

Since the target of this study is short-term scheduling, the most popular and common approach in this term is applying MCS to generate possible scenarios in a day-ahead market by two-stage programming. Nevertheless, multi-segment market, which includes several markets (i.e. day-ahead, intraday, balancing market) together, is used to minimize the effect of forecast errors on scheduling.

Meanwhile, since the novel market DRX is a combination of DR and market, it has a great potential to get developed and extended in an uncertainty environment, especially with a mixture of other short-term markets. DRX still faces a lack of enough experiences in both practical and theoretical viewpoints. Providing proper policies and the definition of its different aspects can be a future research work. Moreover, this study can be extended for long-term energy scheduling in a future work.

Chapter 3

3 Optimal Scheduling of Demand Response in Pre-Emptive Markets Based on Stochastic Bi-level Programming Method

This paper proposes a new strategy for an independent system operator (ISO) to trade demand response (DR) with different DR aggregators while considering various operational constraints. The ISO determines the energy scheduling and reserve deployment in a pre-emptive market while setting DR contracts with the DR aggregators. The ISO applies a two-stage stochastic programming to cope with the uncertainty associated with wind power productions.

DR aggregators' behavior is modeled through profit maximization function. Aggregators determine their DR trading shares with ISO and customers through three DR options including load curtailment, load shifting and load recovery. A stochastic bi-level problem is formulated which in the upper-level, ISO minimizes the total operation cost and in the lower-level, DR aggregator maximizes the profit.

Afterwards, the problem is transferred to a single-level mathematical problem with equilibrium constraints (MPEC) by replacing the lower-level program with its Karush-Kuhn-Tucker (KKT) conditions. As a result, the total operation cost is reduced using the proposed method compared with performing the program without considering the lower-level.

3.1 State-of-the-Art and Aims

EMAND-SIDE management has been widely utilized in electricity markets especially after huge application of smart facilities like intelligent electric devices (IEDs) and advanced metering infrastructures (AMIs). These technologies enable independent system operators (ISOs) to implement demand response (DR) with more details and higher accuracy [151]. Aggregators for performing DR have been introduced to make an easier interaction between customers and ISO.

Likewise, DR aggregators play an important role to achieve all targets of DR implementation such as reducing peak demand, improving the power systems security, decreasing the negative effects caused by the uncertainty of renewable energy sources (RESs) on power system operation and enhancing the economic aspects of electricity market [89]. In fact, DR aggregators serve as interfaces between customers and ISO and enable the participation of customers in the wholesale market [152].

Indeed, DR aggregators face two challenges including with customers in lower-level and with ISO in upper-level. In the upper-level, DR aggregator is challenged in selling DR products to ISO in a contract with the best quantity and the best price. In other words, DR aggregator seeks to define optimal trading options in the wholesale market. In the lower-level, DR aggregator buys DR from customers and looks for implementing DR with the highest profit, while precisely modeling the customers' limitations and constraints.

The best approach for scheduling of power systems from ISO's viewpoint with DR aggregators is considering both levels simultaneously. In other words, once an ISO is running a day-ahead market with DR aggregators, the lower-level (interaction between DR aggregators and customers) and the customers' constraints play an important role to make the final decisions related to DR precisely and economically. Hence, since most of the electricity markets are going to incorporate DR aggregators, considering this approach is desirable. Bi-level programming is one way to formulate both upper and lower-level [153], [154].

A bi-level program can be turned into a single-level mathematical problem by replacing the lower-level problem with its Karush-Kuhn-Tucker (KKT) [155] optimality conditions. Some markets, such as the ones in Singapore, ERCOT, PJM, Alberta, Ontario [156], have already allowed the participation of DR aggregators, and some others, such as Australian National Electricity Market (NEM) [157], are going to allow in the near future. Some researchers have tried to consider DR in the market with the concept of DR aggregators [2], [158]-[160].

In [158], small loads are aggregated to participate in the market for balance management in German balancing mechanism. In [2], domestic appliances of individual customers are considered as bottom-up aggregators which aggregate their reserve bids to offer in the day-ahead reserve market particularly in Portuguese territory reserve market. A game-theoretic framework for interaction between DR aggregators and electricity generators along with DR aggregator and customers is applied, separately to provide profit for all players in [159].

In [160], a bi-level method is applied which in the upper-level, local marginal prices are obtained through performing the unit commitment. In the lower-level, DR is scheduled by minimizing the total operation cost. DR aggregator in [161] solves a two-stage model in which in the first stage, distribution network operator (DNO) minimizes the power loss and in the second stage demand response providers (DRPs) minimize the electricity bill.

Authors in [162] have studied three levels including an operator for the minimization of operation cost, DR aggregator for maximization of profit and end-user for maximization of payoff function. However, the network and its constraints have not been considered, and the problem was solved just by passing and exchanging the reward price to different players.

In [163], the authors only considered the upper-level for optimal hourly DR scheduling in a day-ahead market. They applied four options including load curtailment (LC), load shifting (LS), onsite generation and energy storage (ES) systems. They also implemented these options on lower-level in another work [7] to maximize the DR aggregators' profit.

In [9], the optimal scheduling in day-ahead market has been conducted from wind power producer viewpoint. Indeed, DR aggregators deal with wind power producers in upper-level instead of ISO. In another work [164], a bi-level approach has been applied to consider upper-level including wind power producer-DR aggregator and lower-level including DR aggregator-customer. In upper-level, wind power producer wants to cope with their production uncertainty by making DR contract with DR aggregators. In lower-level, the DR aggregator tries to maximize its revenue.

Reference [165] proposed a bi-level programming for DR scheduling, in which DR aggregator's profit for participation in the day-ahead and real-time markets is maximized in the upper-level, and the cost of providing power balance in the real-time market is minimized in the lower-level. The research in [3] considered both upper-level (ISO-DR aggregator) and lower-level (DR aggregator-customer) separately.

This program has been run in a day-ahead market considering uncertain prices and tried to mix the results of each level to get the optimum solution. They also considered taking a risk using the conditional value-at-risk, although the two levels are not studied at the same time; therefore, the results are not reliable and accurate.

In Table 3.1, key relevant references to the current work are summarized. For each reference, the point of view, the objective function of different levels (if there is any), and the difference (or deficits) of the reference compared with the current work are outlined. Accordingly, there is no study that has optimized the objective functions of ISO and DR aggregators at the same time, in a bi-level programming approach, in the presence of network constraints and considering the uncertainty of wind farms (WFs) from ISO's viewpoint.

A new strategy for an ISO to trade DR with different DR aggregators while considering various operational constraints is proposed in this chapter. ISO determines the energy scheduling and reserve deployment in a pre-emptive market while setting DR contracts with the DR aggregators. ISO applies a two-stage stochastic programming to cope with the uncertainty associated with wind power production.

In this program, ISO makes the day-ahead decisions through having a look at the balancing market. DR aggregators' behavior is modeled through profit maximization function. Aggregators determine their DR trading shares with ISO and customers through three DR options including LC, LS and load recovery (LR). A stochastic bi-level problem is formulated which in the upper-level, ISO minimizes the total operation cost and in lower-level, DR aggregator maximizes the profit. Afterward, the problem is transferred to a single-level mathematical problem with equilibrium constraints through replacing the lower-level program with its Karush-Kuhn-Tucker (KKT) conditions. Moreover, the nonlinearities of the derived problem are linearized through a proposed mathematical method. A 6-bus case study is utilized to assess the proposed strategy.

Table 3.1 Taxonomy of key relevant papers and the differences with the current work

Reference	Viewpoint	Level 1	Level 2	Deficit
[162]	ISO	Minimization of total cost	Maximization of DR aggregators' profit & maximization of customers' payoff	Lack of considering network and its constraints and uncertainty handling
[163]	ISO	Minimization total cost	--	Lack of considering DR aggregator's objective function
[7]	DR Aggregator	--	Maximization the DR aggregator's profit	Lack of considering ISO's objective function
[9]	Wind Power Producer	Minimization negative effect of WF uncertainty	--	- It is not from ISO's viewpoint - Considering just one level without DR aggregator objective function
[164]	Wind Power Producer	Minimization negative effect of WF uncertainty	Maximization the DR aggregator's profit	Lack of being ISO's viewpoint
[165]	DR Aggregator	Maximizing DR aggregator profit for participation in day-ahead market and real-time market	Minimizing cost of power balance in real-time market	- Lack of being ISO's viewpoint - Different objective function in levels
[3]	ISO	Minimization of total cost	Maximization of DR aggregators' profit	Lack of solving two levels at the same time with a bi-level programming

The uncertainty of wind power is considered through generating scenarios in the second stage of upper-level. The main contributions of this chapter are as follows:

- Modeling of the interaction between ISO and DR aggregators as well as the interaction between DR aggregators and customers for short-term scheduling in the presence of WFs.
- Solving a two-stage stochastic programming for minimizing the total operation cost while considering all network constraints as well as WF production scenarios.
- Applying stochastic bi-level programming techniques for solving two objective functions for DR scheduling in a pre-emptive market from ISO's viewpoint.
- Linearizing the dual problem of the lower-level of DR scheduling problem for making decisions by the ISO through a mixed-integer linear programming (MILP) approach.

The remaining parts of the chapter are as follows. Section 3.2 presents the framework of the proposed bi-level model. Section 3.3 provides the corresponding mixed-integer linear problem of upper- and lower-level, the mixed-integer nonlinear problem of the duality of lower-level and its equivalent linear form. Numerical results illustrating the proposed method are provided in Section 3.4. Section 3.5 makes some concluding remarks.

3.2 Problem Statement

In this section, different aspects of the modeling in this chapter are presented. The structure of DR aggregators, their contracts with customers and ISO are explained and formulated. The strategy of ISO for the operation of the network is presented, and the market mechanism and the approach for uncertainty handling are outlined. Finally, the strategy for interaction among ISO, DR aggregator and customers at the same time is expressed as a bi-level model.

3.2.1 DR Aggregator's Perspective

The structure of proposed DR aggregator for the implementing DR scheduling is shown in Figure 3.1. Accordingly, the participation of customers in the electricity market is maximized through DR aggregator in a day-ahead market.

In other words, DR aggregators provide some customer services in order to assess the DR provisions and make the customers aware of their flexible consumption value. Therefore, customers tend to participate in DR more than when they cannot evaluate the profitability of participation in DR. DR aggregators can be the existing market participants such as load/serving entity, distribution network operators or microgrid operators [7].

According to Figure 3.1, DR aggregators are supposed as non-profit independent organizations that each one serves customers located at an especial bus in the transmission network. According to the framework, DR aggregators enroll customers for DR participation and submit DR offers with relative constraints to ISO.

In this model, DR aggregators actively communicate with ISO and customers to take the highest advantages of DR. In the day-ahead market for starting DR programs; ISO starts the DR programs through sending the required information to aggregators to register their DR bids. ISOs and DR aggregators can utilize a variety of systems and technologies to communicate demand response signals, ranging from internet-based protocols to dedicated networks communicating via DNP3.

Moreover, the NAESB WEQ standards include requirements for all data flow from registration through to performance evaluation of demand sources involving deployment. Automated demand response (AutoDR) communication protocols, which are designed especially for large electricity customers and industrial customers, can be utilized for this purpose as well. DR aggregators design the proper contract schemes for the customer and assess the DR capability of loads to help them for qualification themselves to participate in DR programs.

The contract between DR aggregator and customer is made based on DR aggregator bids which are defined according to the assessment conducted on customers' capabilities in DR participation. Likewise, a range of load reduction quantity is determined in the contract, based on customers' physical load reduction strategies.

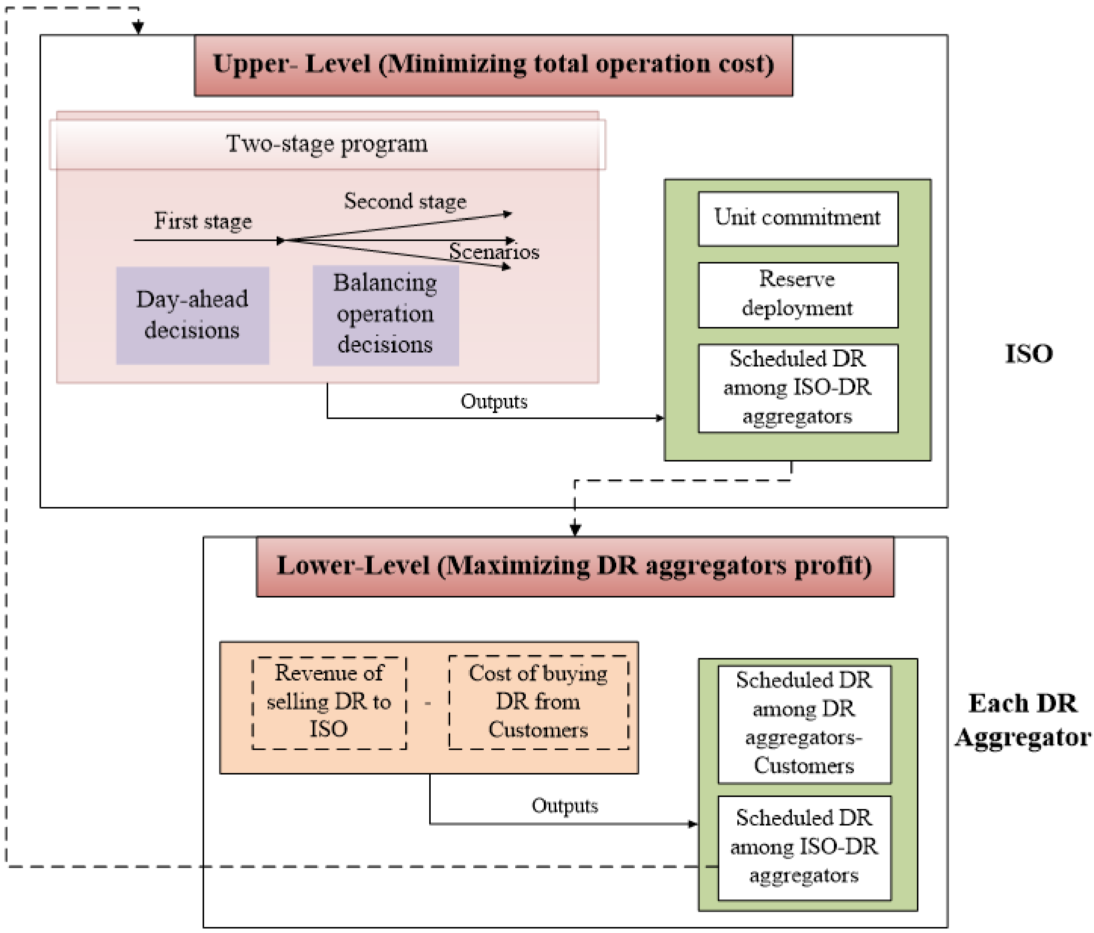


Figure 3.1. Proposed bi-level model.

In the next stage, aggregators run DR contracts in day-ahead market to define optimal DR offer through maximizing their profit, and this data will be sent to ISO [7]. In the current chapter, DR aggregators form DR offers of three load reduction options including LC, LS, and LR are considered.

3.2.2 ISO's Perspective

In this chapter, the network is supposed to include renewable energy sources like WFs; therefore, the stochastic nature of wind power production should be modeled in a scenario-based method to show the possible events in the real-time.

Wind speed is an uncertain variable followed by unpredictable power generation of wind power generator. Wind speed profile in one area is conformed approximately to the Rayleigh distribution [36]. To form the probability distribution function (PDF), some parameters should be calculated from given historical data processing [101], [166].

The equation of converting wind speed to electric power is a linear one extracted from [101]. Based on Monte-Carlo Simulation method (MCS) and using constructed Rayleigh PDF, several scenarios are generated to illustrate the behavior of wind power generator in real-time. To this end, a uniform random variable is generated and assigned to the mentioned PDF. Afterwards, a wind speed with a probability is obtained followed by the amount of wind power generation. Finally, with a scenario reduction method (forward method) the desired amount of scenarios can be achieved. This procedure is demonstrated in Figure 3.2.

Based on Figure 3.1, ISO runs a pre-emptive market which describes an interaction among day-ahead market and balancing market [121]. This market framework can cope with the uncertainty of renewable generation why enough flexible capacity is made available for balancing through day-ahead energy reserve dispatch. The structure can be seen in Figure 3.1.

In fact, day-ahead energy dispatch decisions account for balancing operation through different scenarios which contain possible events in real-time [121]. ISO receives generating companies (GENCOs) offers for energy and up/down reserve. ISO also receives the DR offers from DR aggregators, and when the ISO clears the market, hourly DR scheduling will be sent to DR aggregators.

DR options, strategies and framework proposed to ISO are similar to ones are proposed to customers by DR aggregators. A two-stage stochastic model is applied for short-term scheduling. The first-stage decisions are those made for day-ahead market including energy and reserve of GENCOs as well as DR scheduling for aggregators in each scheduling hour. The second-stage decisions are those that related to the realization of scenarios including the deployment of the reserve, force load reduction and wind spillage.

3.2.3 Demand Response Options

DR aggregator can be designed for a specific class of customers [163], however, in this chapter; we consider a comprehensive DR aggregator scheme which considers all customers and causes further reduction in a number of DR correspondence with consumers. Three load reduction strategies including LC, LS, and LR are utilized as DR options to participate in the day-ahead market and are expressed below.

3.2.3.1 Load Curtailment

In LC option, customers reduce their consumption based on the program without shifting to other hours [7], [163]. The LC contracts include a number of offers k which each offer has a specific price according to an agreement among ISO and DR aggregators $DR_{tnk}^{Cost,LC}$ or DR aggregator and customers $B_{tnk}^{Cost,LC}$. The DR cost is non-linear, however we apply price-quota curve approach for linearization and the customers react to different prices in a stepwise way. The price of each step is constant and the quantity is a decision variable in a special range for each step.

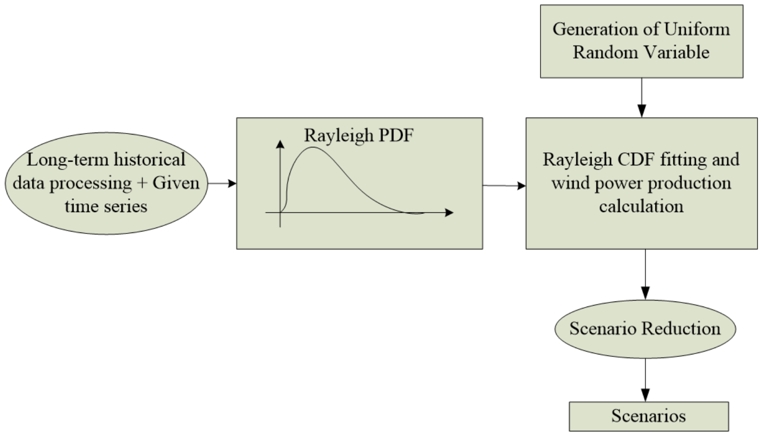


Figure 3.2. Scenario generation flowchart.

The stepwise function is shown in Figure 3.3. A similar price pattern is obtained for LS and for the lower-level contract between DR aggregators and customers. Accordingly, the higher incentive the aggregator offers, the higher volume of load reduction will be selected by customers.

The LC contract also has a maximum and minimum quantity of load curtailment for each LC offer which is in equation (3.2) where u_{tnk}^{LC} is a binary variable to show if the LC offer is scheduled (equal to 1). The exact volume of LC quantity DRK_{tnk}^{LC} of offer k at time t for LC option is scheduled for DR aggregator bus n and the total cost for LC will be obtained by equation (3.1).

Equation (3.3) indicates when the offer t will be started $y_{tnk}^{LC} = 1$ and when it will be terminated $z_{tnk}^{LC} = 1$. Equation (3.4) is for preventing any coincidence in starting and terminating. Minimum and maximum durations of load reduction are in equations (3.5) – (3.6) and the maximum number of LC in a day is given in equation (3.7).

3.2.3.2 Load Shifting and Load Recovery

In LS option, customers' loads are curtailed with the potential of shifting to another time within the same day [7], [163]. The shifting and supplying total volume of curtailed loads with the potential of shifting (as LS) will be conducted in other hours of the day as an LR option.

The modeling of LS contract is similar to LC which is given in equations (3.1) – (3.7) $(\hat{X} \in LS)$. The modeling of a combination of LS and LR is presented in (3.8) – (3.10). According to equation (3.8), the volume of LR offer k at time t, DRK_{tnk}^{LR} has a limitation and should be lower than a specific amount defined in the contract. Moreover, as equation (3.10) shows, the total volume of LS in a day should be equal the total volume of LR. Meanwhile, the LR and LS should not be taken place at the same time given in equation (3.9). In fact, LS presents how much load can be shifted in a certain peak time, while LR manages and controls to recover shifted loads through its precise program in order to avoid peak demand in off-peak hours and wind power spillage, especially in the morning when the wind speed is usually high.

$$CDR_{tn}^{\hat{X}} = \sum_{k \in KD} DRK_{tnk}^{\hat{X}} \times DR_{tnk}^{Cost,\hat{X}} \tag{3.1}$$

$$DRK_{tnk}^{Min,\hat{X}} \times u_{tnk}^{\hat{X}} \le DRK_{tnk}^{\hat{X}} \le DRK_{tnk}^{Max,\hat{X}} \times u_{tnk}^{\hat{X}} \tag{3.2}$$

$$u_{tnk}^{\hat{X}} - u_{t-1nk}^{\hat{X}} = y_{tnk}^{\hat{X}} - z_{tnk}^{\hat{X}} \tag{3.3}$$

$$y_{tnk}^{\hat{X}} + z_{tnk}^{\hat{X}} \le 1 \tag{3.4}$$

$$\sum_{t}^{t+LCD_{nk}^{\max,LC}-1} z_{tnk}^{\hat{X}} \ge y_{tnk}^{\hat{X}} \tag{3.5}$$

$$\sum_{t}^{t+LCD_{nk}^{\min}-1} u_{tnk}^{\hat{X}} \ge LCD_{nk}^{\hat{X},\min} \times (u_{tnk}^{\hat{X}} - u_{t-1nk}^{\hat{X}}) \tag{3.6}$$

$$\sum_{t} y_{tnk}^{\hat{X}} \le MC_{nk}^{\hat{X}} \tag{3.7}$$

$$DRK_{tnk}^{LR} \le DRK_{tnk}^{\max,LR} \times u_{tnk}^{LR} \tag{3.8}$$

$$u_{tnk}^{LR} + u_{tnk}^{LS} \le 1 \tag{3.9}$$

$$\sum_{t \in TR} DRK_{tnk}^{LR} = \sum_{t \in TS} DRK_{tnk}^{LS} \tag{3.10}$$

3.2.4 Bi-level Model

The decision-making problem pertaining to system operations that jointly minimizes the total operation cost and maximizes the DR aggregator profit can be formulated as a bi-level programming problem. The upper-level problem deal with decisions to be made by ISO with the goal of reducing operation cost in the presence of different DR options and considering different wind production scenarios for increasing system security

The lower-level problem represents decisions to be made by DR aggregator and related to DR offers in contracts among ISO-DR aggregators as well as DR aggregators-customers with the target of maximization of DR aggregator profit. Since contracts among ISO-DR aggregators are in both upper- and lower-level, they will be scheduled at the same time through this proposed bi-level stochastic programming. The structure of this strategy and the interaction among different players are illustrated in Figure 3.4.

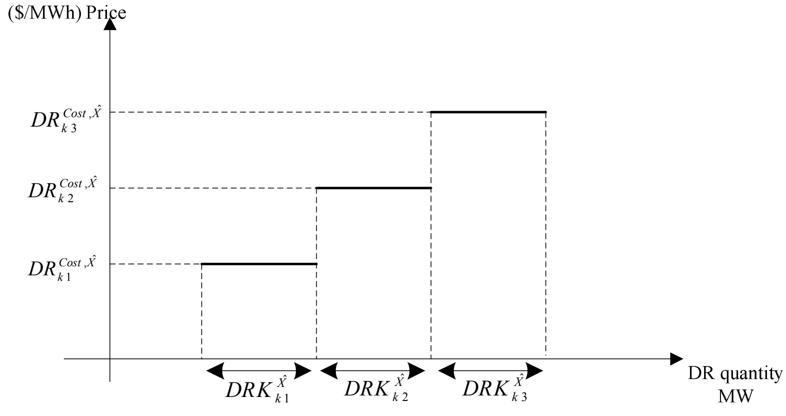


Figure 3.3. DR price bidding.

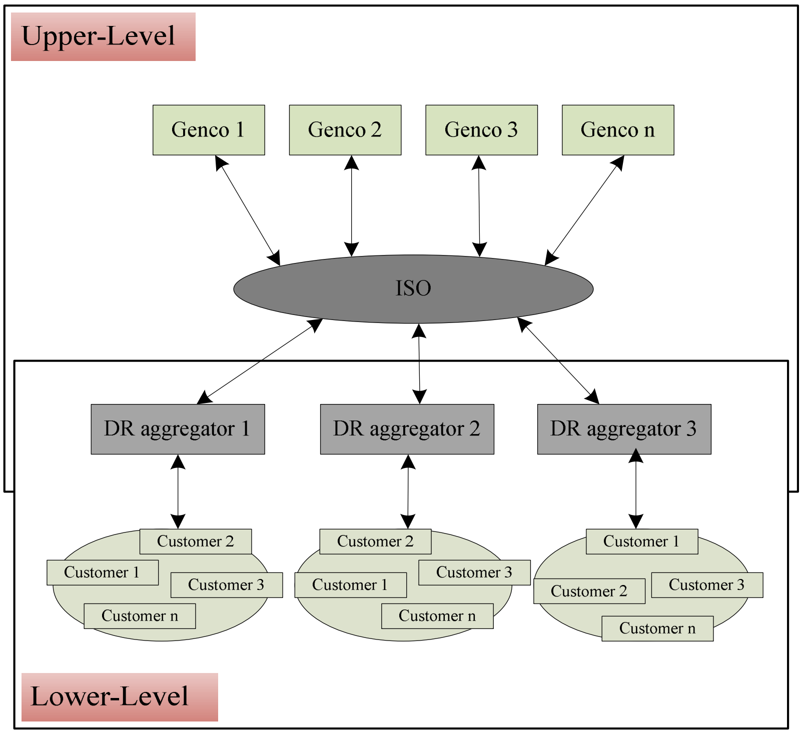


Figure 3.4. Interaction among different players.

3.3 Problem Formulation

The stochastic day-ahead operation scheduling can be formulated as the stochastic bi-level model below:

3.3.1 Bi-level Programming

According to Figure 3.1, the upper-level is the minimization of total operation cost through a stochastic two-stage programming as MILP problem which the objective function is in equation (3.11) and constraints are in equations (3.12) – (3.38).

The first and the second line of equation (3.11) is respect to first-stage of the program (here-and-now or day-ahead decisions) which includes generation cost of units, start-up and shut-down cost, units' capacity cost of up- and down- reserve as well as total cost of demand response options (LS and LC). The third and forth line of (3.11) are linked to second-stage of the program (wait-and-see or balancing operation decisions) [121] which includes the energy cost of units' up- and down- reserve with wind spillage cost and forced load shedding in all scenarios.

First-stage constraints are in equations (3.12) – (3.23); equations (3.12) – (3.13) are maximum/minimum capacity limitation of units. Day-ahead balance equation is in (14); units' up-/down- reserve limitations are in equations (3.15) – (3.16); units' ramp-up and down constraints are given in equations (3.17) –(3.18); equations (3.19) – (3.20) represent the constraints that define the units' start-up/shut-down costs.

DC power flow equation is presented in (3.21), and the transmission line capacity is in equation (3.22); equation (3.23) defines that the amount of scheduled wind power should be less than the expected volume which is the forecasted amount of wind power. Meanwhile, equations (3.1) – (3.10) are applied for calculation of DR costs that ISO should pay to DR aggregators in the day-ahead market.

The second-stage constraints are in equations (3.24) – (3.29); equation (3.24) is the balancing condition for real-time market; DC power flow equations for real-time are shown in equations (3.25) – (3.26); wind-spillage should be lower than wind power of each scenario which is shown in equation (3.27); limitations of up-/down-reserve for each scenario are shown in equations (3.28) – (3.29).

The lower-level formulations are given in equations (3.30) – (3.44). The objective function, the maximization of DR aggregator profit as a linear problem, is given in equation (3.30); the first line of equation (3.30) is the revenue of DR aggregator from selling DR offers to ISO and the second line is the DR aggregators' expenditures of purchasing DR from customers.

The constraints described in equations (3.31) –(3.37) are for selling DR to ISO and constraints described in equations (3.38) – (3.44) are related to buying DR from customers.

$$\begin{aligned} & Minimize \sum_{t\in NT} \Bigg\{ \sum_{g\in NG} (C_{tg}^{gen} \times P_{tg}^{gen} + SUC_{tg}^{gen} + C_{tg}^{up} \times R_{tg}^{up} + C_{tg}^{down} \times R_{tg}^{down}) \\ & + \sum_{n\in NN} (CDR_{tn}^{LC} + CDR_{tn}^{LS}) \\ & + \sum_{s\in S} \pi_s \Bigg[\sum_{g\in NG} (Cs_{tgs}^{up} \times Rs_{tgs}^{up} + Cs_{tgs}^{down} \times Rs_{tgs}^{down}) \\ & + \sum_{n\in NN} (Cs_{tns}^{spill} \times W_{tns}^{spill} + Cs_{tns}^{voll} \times Ls_{tns}^{shed}) \Bigg] \Bigg\} \end{aligned} \tag{3.11}$$

In (3.11), the here-and-now decision variables are P_{tg}^{gen}, SUC_{tg}^{gen}, R_{tg}^{up}, R_{tg}^{down}, CDR_{tn}^{LC}, CDR_{tn}^{LS}, and the wait-and-see decision variables include Rs_{tgs}^{up}, Rs_{tgs}^{down}, W_{tns}^{spill}, Ls_{tns}^{shed}. These variables are defined through minimizing (3.11) with considering following constraints:

$$P_{tg}^{gen} + R_{tg}^{up} \le P_g^{\max} \times u_{tg}^{gen} \tag{3.12}$$

$$P_{tg}^{gen} - R_{tg}^{down} \ge P_g^{\min} \times u_{tg}^{gen} \tag{3.13}$$

$$\sum_{g\in NG} p_{tg}^{gen} + W_{tn}^{sch} + \sum_{k\in KD} (DRK_{tnk}^{LC} + DRK_{tnk}^{LS} - DRK_{tnk}^{LR}) = LD_{tn} + \sum_{l\in NL} pf_{tl} \tag{3.14}$$

$$0 \le R_{tg}^{up} \le R_g^{\max,up} \tag{3.15}$$

$$0 \le R_{tg}^{down} \le R_g^{\max,down} \tag{3.16}$$

$$P_{t-1g}^{gen} - P_{tg}^{gen} \le Rmp_g^{up} \tag{3.17}$$

$$P_{tg}^{gen} - P_{t-1g}^{gen} \le Rmp_g^{down} \tag{3.18}$$

$$SUC_{tg}^{gen} \ge C_g^{strt.up} \times (u_{tg}^{gen} - u_{t-1g}^{gen}) \tag{3.19}$$

$$SUC_{tg}^{gen} \geq C_{g}^{sht.dwn} \times (u_{t-1g}^{gen} - u_{tg}^{gen}) \tag{3.20}$$

$$pf_{tl} = \sum_{n\in NN} \frac{1}{X_{nl}} \times (\theta_{nl}^{1} - \theta_{nl}^{0}), \quad -2\pi \leq \theta_{nl} \leq 2\pi \tag{3.21}$$

$$pf_{l}^{\min} \leq pf_{tl} \leq pf_{l}^{\max} \tag{3.22}$$

$$0 \leq W_{tn}^{sch} \leq W_{tn}^{\exp} \tag{3.23}$$

$$\sum_{g\in NG} (Rs_{tgs}^{up} - Rs_{tgs}^{down}) + W_{tns}^{scen} - W_{tn}^{sch} - W_{tns}^{spill} + Ls_{tns}^{shed} = -\sum_{l\in NL} (pfs_{tls} - pf_{tl}) \tag{3.24}$$

$$pfs_{tls} = \sum_{n\in NN} \frac{1}{X_{nl}} \times (\theta_{nls}^{1} - \theta_{nls}^{0}), \quad -2\pi \leq \theta_{nls} \leq 2\pi \tag{3.25}$$

$$pf_{l}^{\min} \leq pfs_{tls} \leq pf_{l}^{\max} \tag{3.26}$$

$$0 \leq W_{tns}^{spill} \leq W_{tns}^{scen} \tag{3.27}$$

$$0 \leq Rs_{tgs}^{up} \leq R_{tg}^{up} \tag{3.28}$$

$$0 \leq Rs_{tgs}^{down} \leq R_{tg}^{down} \tag{3.29}$$

Where:

$$\begin{aligned} &Maximize \sum_{t\in NT} \sum_{n\in NN} \sum_{k\in KD} (DRK_{tnk}^{LC} \times DR_{tnk}^{Cost,LC} + DRK_{tnk}^{LS} \times DR_{tnk}^{Cost,LS}) \\ &-(DBK_{tnk}^{LC} \times DB_{tnk}^{Cost,LC} + DBK_{tnk}^{LS} \times DB_{tnk}^{Cost,LS}) \end{aligned} \tag{3.30}$$

subject to:

$$DRK_{tnk}^{LC} \leq DRK_{tnk}^{Max,LC} \times u_{tnk}^{LC} : \alpha_{tnk} \tag{3.31}$$

$$-DRK_{tnk}^{LC} \leq -DRK_{tnk}^{Min,LC} \times u_{tnk}^{LC} : \beta_{tnk} \tag{3.32}$$

$$DRK_{tnk}^{LS} \leq DRK_{tnk}^{Max,LS} \times u_{tnk}^{LS} : \gamma_{tnk} \tag{3.33}$$

$$-DRK_{tnk}^{LS} \leq -DRK_{tnk}^{Min,LS} \times u_{tnk}^{LS} : \lambda_{tnk} \tag{3.34}$$

$$DRK_{tnk}^{LR} \leq DRK_{tnk}^{\max,LR} \times u_{tnk}^{LR} : \zeta_{tnk} \tag{3.35}$$

$$u_{tnk}^{LR} + u_{tnk}^{LS} \leq 1 \tag{3.36}$$

$$\sum_{t\in TR} DRK_{tnk}^{LR} = \sum_{t\in TS} DRK_{tnk}^{LS} : \mu_{tnk} \tag{3.37}$$

$$DBK_{tnk}^{LC} \leq DBK_{tnk}^{Max,LC} \times u_{tnk}^{LC} : \sigma_{tnk} \tag{3.38}$$

$$-DBK_{tnk}^{LC} \leq -DBK_{tnk}^{Min,LC} \times u_{tnk}^{LC} : \rho_{tnk} \tag{3.39}$$

$$DBK_{tnk}^{LS} \leq DBK_{tnk}^{Max,LS} \times ub_{tnk}^{LS} : \varphi_{tnk} \tag{3.40}$$

$$-DBK_{tnk}^{LS} \leq -DBK_{tnk}^{Min,LS} \times ub_{tnk}^{LS} : \tau_{tnk} \tag{3.41}$$

$$DBK_{tnk}^{LR} \leq DBK_{tnk}^{\max,LR} \times ub_{tnk}^{LR} : \varepsilon_{tnk} \tag{3.42}$$

$$ub_{tnk}^{LR} + ub_{tnk}^{LS} \leq 1 \tag{3.43}$$

$$\sum_{t\in TR} DBK_{tnk}^{LR} = \sum_{t\in TS} DBK_{tnk}^{LS} : \omega_{tnk} \tag{3.44}$$

3.3.2 Implementing Duality Theory

In the bi-level problem, the lower-level problem can be turned into its dual problem. Since each primal constraints of the lower-level problem from equations (3.30) – (3.44) is continuous and convex, it can be represented by its dual constraints and strong duality conditions [153].

The nonlinear dual problem of the lower level and its dual constraints beside strong duality conditions are given in equations (3.45) – (3.50). The nonlinear problem from equation (3.45) can be transferred to the linear problem through equations (3.51) – (3.54). Equation (3.51) defines all nonlinear items which are a multiplication of a binary variable and positive variable like $\alpha_{tnk}u_{tnl}^{LC}$ as a single positive variable like α'_{tnk}.

In equation (3.52) a boundary is defined for the new variable α'_{tnk} where SPP_{tnk} is a large enough quantity compared with a range of α'_{tnk} (about more than 10 times). u'^{LC}_{tnk} is a new binary variable which determines if new variables (e.g. α'_{tnk}) are zero or equal to former variables (e.g. α_{tnk}).

Equation (3.52) determines that if $u'^{LC}_{tnk} = 0$, the variable $\alpha'_{tnk} = 0$, and consequently $\alpha_{tnk} = 0$. Equations (3.53) – (3.54) specify that if $u'^{LC}_{tnk} = 1$, then $\alpha'_{tnk} = \alpha_{tnk}$. Therefore, the dual problem of lower-level will be turned into a linear problem.

$$\begin{aligned} & Minimize \sum_{t\in NT}\sum_{n\in NN}\sum_{k\in KD} \alpha_{tnk}\times u_{tnk}^{LC}\times DRK_{tnk}^{Max,LC} - \beta_{tnk}\times u_{tnk}^{LC}\times DRK_{tnk}^{Min,LC} \\ & +\gamma_{tnk}\times u_{tnk}^{LS}\times DRK_{tnk}^{Max,LS} - \lambda_{tnk}\times u_{tnk}^{LS}\times DRK_{tnk}^{Min,LS} + \zeta_{tnk}\times u_{tnk}^{LR}\times DRK_{tnk}^{\max,LR} \\ & +\sigma_{tnk}\times ub_{tnk}^{LC}\times DBK_{tnk}^{Max,LC} - \rho_{tnk}\times ub_{tnk}^{LC}\times DBK_{tnk}^{Min,LC} \\ & +\varphi_{tnk}\times ub_{tnk}^{LS}\times DBK_{tnk}^{Max,LS} - \tau_{tnk}\times ub_{tnk}^{LS}\times DBK_{tnk}^{Min,LS} + \varepsilon_{tnk}\times ub_{tnk}^{LR}\times DBK_{tnk}^{\max,LR} \end{aligned} \tag{3.45}$$

subject to:

$$\alpha_{tnk} - \beta_{tnk} \ge DR_{tnk}^{Cost,LC} \tag{3.46}$$

$$\gamma_{tnk} - \lambda_{tnk} \ge DR_{tnk}^{Cost,LS} \tag{3.47}$$

$$\sigma_{tnk} - \rho_{tnk} \ge -DB_{tnk}^{Cost,LC} \tag{3.48}$$

$$\varphi_{tnk} - \tau_{tnk} \ge -DB_{tnk}^{Cost,LS} \tag{3.49}$$

$$\alpha_{tnk}, \beta_{tnk}, \gamma_{tnk}, \lambda_{tnk}, \sigma_{tnk}, \rho_{tnk}, \varphi_{tnk}, \tau_{tnk} \ge 0 \tag{3.50}$$

Linearization:

$$\alpha_{tnk}\times u_{tnk}^{LC} = \alpha'_{tnk} \quad .... \quad \varepsilon_{tnk}\times ub_{tnk}^{LR} = \varepsilon'_{tnk} \tag{3.51}$$

$$\alpha'_{tnk} \le SPP_{tnk}\times u'^{LC}_{tnk} \quad .... \quad \varepsilon'_{tnk} \le SPP_{tnk}\times u'^{LR}_{tnk} \tag{3.52}$$

$$\alpha'_{tnk} \le \alpha_{tnk} + SPP_{tnk}\times(1-u'^{LC}_{tnk}) \quad ..... \quad \varepsilon'_{tnk} \le \varepsilon_{tnk} + SPP_{tnk}\times(1-u'^{LR}_{tnk}) \tag{3.53}$$

$$\alpha'_{tnk} \ge \alpha_{tnk} - SPP_{tnk}\times(1-u'^{LC}_{tnk}) \quad ... \quad \varepsilon'_{tnk} \ge \varepsilon_{tnk} - SPP_{tnk}\times(1-u'^{LR}_{tnk}) \tag{3.54}$$

3.3.3 Equivalent Single-Level Problem

The stochastic bi-level problem of equations (3.11) – (3.44) can be turned into stochastic one-level problem through incorporating primal constraints of lower-level and its dual strong condition and constraints into upper-level.

The strong duality theorem states that a feasible solution of the primal problem and dual problem are obtained if and only if primal and dual objective functions are equal [155]:

$$\begin{aligned}
&\sum_{t\in NT}\sum_{n\in NN}\sum_{k\in KD}(DRK_{tnk}^{LC}\times DR_{tnk}^{Cost,LC}+DRK_{tnk}^{LS}\times DR_{tnk}^{Cost,LS})\\
&-(DBK_{tnk}^{LC}\times DB_{tnk}^{Cost,LC}+DBK_{tnk}^{LS}\times DB_{tnk}^{Cost,LS})=\\
&\sum_{t\in NT}\sum_{n\in NN}\sum_{k\in KD}\alpha'_{tnk}\times DRK_{tnk}^{Max,LC}-\beta'_{tnk}\times DRK_{tnk}^{Min,LC}\\
&+\gamma'_{tnk}\times DRK_{tnk}^{Max,LS}-\lambda'_{tnk}\times DRK_{tnk}^{Min,LS}+\zeta'_{tnk}\times DRK_{tnk}^{\max,LR}\\
&+\sigma'_{tnk}\times DBK_{tnk}^{Max,LC}-\rho'_{tnk}\times DBK_{tnk}^{Min,LC}\\
&+\varphi'_{tnk}\times DBK_{tnk}^{Max,LS}-\tau'_{tnk}\times DBK_{tnk}^{Min,LS}+\varepsilon'_{tnk}\times DBK_{tnk}^{\max,LR}
\end{aligned}\tag{3.55}$$

Single-level mixed integer linear problem equivalent to (3.11) – (3.44) is achieved by minimizing the upper-level objective function and considering all upper-level constraints as well as primal and dual constraints of lower-level constraints which are given below.

$$Minimize\ (3.11)\tag{3.56}$$

subject to :

$$equations\ (3.1) – (3.10),\ (3.12) – (3.29);\ \text{and,}\tag{3.57}$$

$$equations\ (3.31) - (3.44),\ (3.46) - (3.55).\tag{3.58}$$

3.4 Numerical Studies

A 6-bus system is applied to evaluate the proposed model in this section; however, the model has been successfully tested on larger systems such as IEEE 24-bus system. The system shown in Figure 3.5 includes 3 conventional generation units and a WF with the maximum capacity of 20 MW. Each bus connected to load demands has a DR aggregator.

Three cases are considered to study the different states of this problem. The cases contain DR Price variation to show the effect of DR price on the outputs. In each case, the proposed model is compared with the case when DR aggregator-customer contract is not considered which we called here as being the model disregarding DR aggregator’s viewpoint (DDRV).

In other words, since the proposed method has two levels and the second level is from DR aggregator's viewpoint, in DDRV, the second level has been omitted and only the first level, which is the minimization of the total operation cost with DR options, has been considered.

Hence, the impact of simultaneously considering ISO-DR aggregator contract and DR aggregator-customer contract is investigated versus considering only ISO-DR aggregator contracts, demonstrating the merits of the proposed model.

Case 1 includes the main price scheme, which is placed as a reference to compare other cases. In case 2, the DR prices are 20% higher than the first case, and in case 3, conversely, DR Price is 20% lower than case 1. DR offer prices for load reduction of case 1 are categorized in Table 3.2, DRC is relevant to DR offers of the ISO-DR aggregator contract, and DBC is related to offers of DR aggregators-customers contract.

These DR prices are identified based on the price difference between selling and buying DR in the upper level and lower level. In fact, DR aggregator should take the advantages of DR price difference when buying from the customer and selling to ISO. Hence, the DR selling price has to be more than the DR buying price so that the DR aggregator can benefit from this market.

These offers for all DR aggregators are the same. Other information about constraints of DR offers and options as well as 6-bus case study data are given in [167]. The problem is solved by solver CPLEX in GAMS [168] using a computer with 6GB RAM and 2.6GHz, core i7 processor. The computation time is less than 1 second.

The impact of the proposed model on load profile for the case 1 is demonstrated in Figure 3.6 As can be seen, after running DR programs, LC, LS, and LR are applied to the load profile. Between hours 10 to 18, LR and LS are called. Therefore, the load curve for peak hours is shaved.

However, this LC for proposed model is more than when just interaction between ISO and DR aggregator is considered as a DDRV method. The reason behind this is why unlike the DDRV method, in the proposed model is considering the interaction of both ISO-DR aggregator and DR aggregator-customer. Hence, the model includes the detail information of DR aggregator contract with customers, and it gives more precise results.

Moreover, the curtailed loads are shifted to off-peak hours between hours 1 to 8 and customers will consume their voluntary curtailed load in off-peak hours as LS and LR options. As a result of the previous phenomenon for LC, more load demands are shifted and recovered to the off-peak hours through the proposed model in compared with the DDRV method.

In Table 3.3, the impact of the proposed model on unit commitment in case 1 is illustrated. Accordingly, by implementing the proposed bi-level model, there is no need for committing the generator number 2 until hour 11.

It causes a decrease in energy cost which is units' generation and reserve cost following by a drop in total operation cost which is demonstrated in Table 3.5, which is due to the fact that since the proposed model has a closer look at details of customer constraints and decision-making variables, the cheapest unit (G1) produces more power in proposed model to supply the both shifted and regular loads.

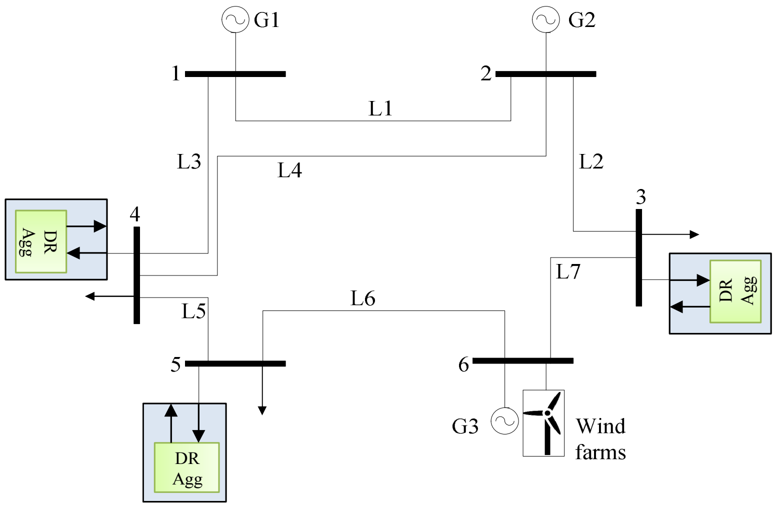


Figure 3.5. One-line diagram of studied 6-bus network.

Table 3.2 DR prices for 5 offers and two options in case 1.

CASE1		K1 (€/MWh)	K2 (€/MWh)	K3 (€/MWh)	K4 (€/MWh)	K5 (€/MWh)
DRC	LC price	10	11	12	13	14
	LS Price	10	11	12	13	14
DBC	LC price	8	9	10	11	12
	LS Price	8	9	10	11	12

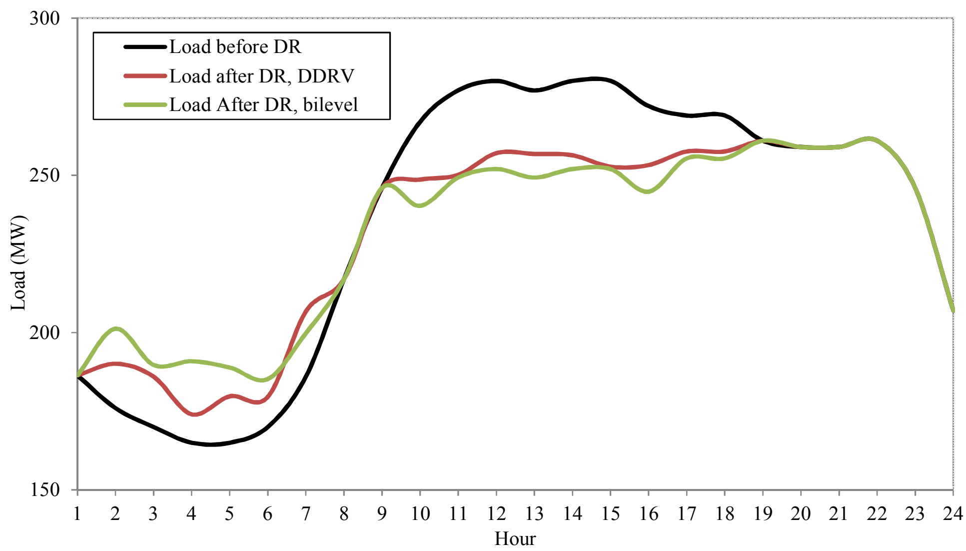


Figure 3.6. Impact of proposed DR model on load profile for case 1.

In the second case, with increasing the DR offer price for both ISO-DR aggregator contracts and DR aggregator-customers, no change for load reduction is taken place based on Figure 3.7. However, it was expected that higher DR price leads to less scheduled load reduction. Therefore, it can be concluded that increasing DR price at least up to 20% has no negative impact on customers' DR participation.

Moreover, the amount of load that should be recovered based on LR at each off-peak hour is different in case 2 compared with case 1 for both DDRV and the proposed method. Because according to the model, the consumption can be freely shifted to each off-peak hour up to 2MW. Hence, loads are generally shifted to hours with more generation.

For example, at hour 5, G1 generates 193.78MW in case 2 in the proposed bi-level model, while this generation is 187.69MW in case 1. Therefore, as can be seen in Figure 3.7, the recovered loads at hour 5 in case 2 are more than this volume in case 1. In addition, there is no difference between unit commitment status of case 1 and case 2.

Because the higher DR price does not aid to improve the system operation condition. As it was expected, the higher price for DR offer is considered, the higher total operation cost, DR implementation cost and energy cost take place which is illustrated in Table 3.5.

The load profile in case 3 for the proposed bi-level model has no remarkable changes compared with cases 1 and 2. This reflects the fact that DR price variation within ±20% has no impact on load reduction pattern for the proposed method. On the other hand, the load reduction in DDRV method in case 3 at hour 11 is less than case 1 and case 2 according to Figure 3.8, while the DR price in case 3 is lower and the load reduction is supposed to be equal or more than other cases.

The reason is due to the lack of enough accuracy for DDRV model. Another difference is in the amount of load that is shifted and recovered at hours 1 to 8 which the reason can be explained similar to what happens in case 1 and case 2 in this term. On the other hand, in this case, according to the Table 3.4, the unit commitment status in both conventional method and the proposed bi-level method is the same. Because the DR price is low and it is better to apply DR instead of turning on generators even for DDRV.

In other words, unlike the case 1, generator number 2 is not scheduled and committed for the first 8 hours even in the DDRV method. Moreover, according to the Table 3.5, the total operation cost of two methods in case 3 are relatively the same. It is concluded that low price of DR offers is not able to demonstrate the positive impact of the proposed bi-level method, because in reality, too low DR prices cannot be reasonable and applicable for DR implementation.

Security cost, which is the cost of dealing with balancing market scenarios in the second stage, is lower in the proposed bi-level method in case 1 and 2; however, this cost is the same in the third case based on Table 3.5. A sensitivity analysis for DR prices is conducted for the proposed model which is demonstrated in Figure 3.9 Accordingly, case 1 is assumed as the base of DR price.

Table 3.3 Unit commitment status of units' comparison among proposed bi-level model and conventional method for case 1

Unit	DDRV Method (Hours 1 to 24)
G1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
G2	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
G3	0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Unit	**Proposed Bi-level Method (Hours 1 to 24)**
G1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
G2	0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1
G3	0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

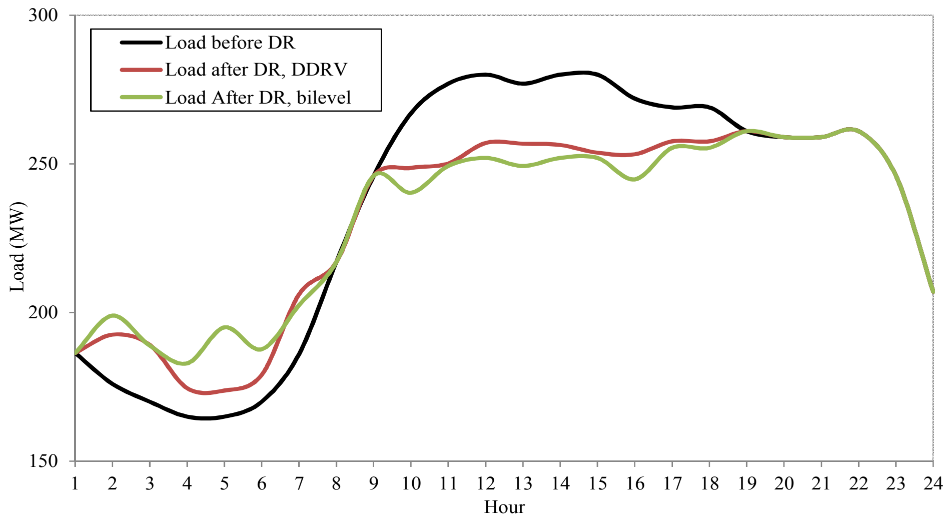


Figure 3.7. Impact of proposed DR model on load profile for case 2.

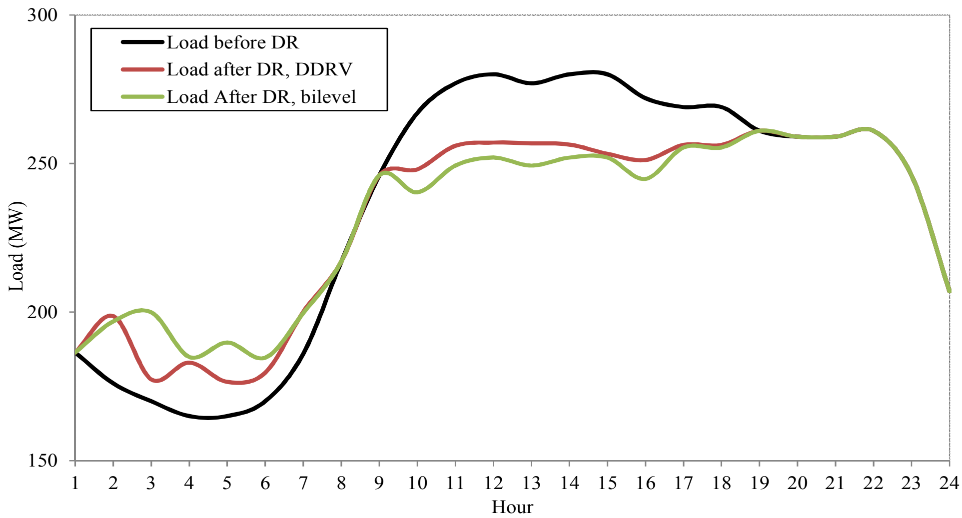


Figure 3.8. Impact of proposed DR model on load profile for case 3.

Table 3.4 Unit commitment status of units' comparison among proposed bi-level model and conventional method for case 3

Unit	DDRV Method (Hours 1 to 24)
G1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
G2	0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1
G3	0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Unit	**Proposed Bi-level Method (Hours 1 to 24)**
G1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
G2	0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1
G3	0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

Table 3.5 Different costs in all cases based on two methods

Case	Method	Total Operation Cost (€)	Energy Cost (€)	Security Cost (€)	DR cost (€)
Case1	DDRV	90158	88878	862	2142
	Bi-level	88475	86664	835	2646
Case2	DDRV	90574	88881	862	2554
	Bi-level	89004	86664	835	3175
Case3	DDRV	87740	86876	835	1699
	Bi-level	87946	86664	835	2117

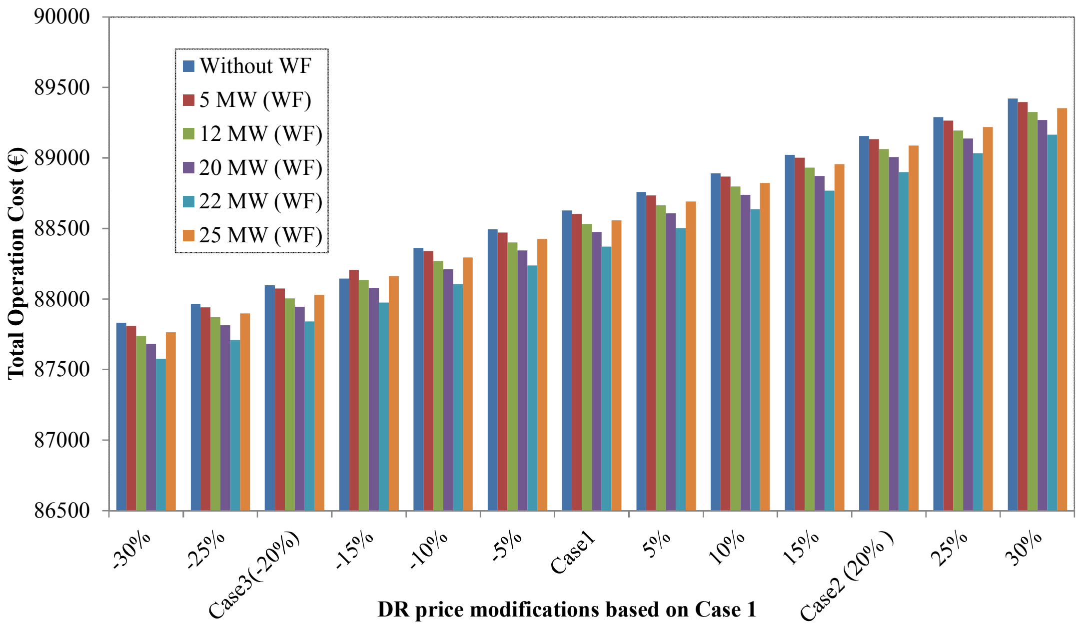


Figure 3.9. The impact of DR prices and WF capacity on total operation cost.

On one hand, the DR price will increase from 5% to 30% of DR price of case1, and on the other hand, it will decrease from 5% to 30% of DR price. Meanwhile, the impact of different WF maximum capacities is studied. As expected, with increasing DR prices, total operation cost generally grows for each WF capacity. Moreover, the larger WF is installed, the lower total operation cost is obtained. However, installing more than 22MW WF will cause an increase in total operation cost due to increase the wind spillage cost.

3.5 Brief Remarks of the Chapter

A stochastic bi-level problem has been formulated in which the upper-level problem aims to minimize the total operation cost of the ISO and the lower-level problem seeks the maximum profit of DR aggregators. A two-stage stochastic programming is applied to cope with the uncertainty of wind power production.

DR aggregators' behavior was modeled through profit maximization functions. Aggregators determine their DR trading shares with ISO and customers through three DR options, namely LC, LS, and LR. Comparisons among the proposed bi-level model and the DDRV method as well as different prices for DR offers were performed in a 6-bus system.

The results demonstrated that the proposed method could reduce more loads in peak hours followed by more load recovery in off-peak hours. Moreover, the total cost was reduced compared with the DDRV method. These improvements and differences among the proposed bi-level method and DDRV method are due to the fact that scheduling in the proposed method was performed based on more information related to DR and had a closer look at details of customer constraints.

However, when the prices of DR offers were low, there was no remarkable difference between operation costs in the proposed method and DDRV method. Likewise, the operation cost was reduced when a higher capacity of WF was used; however, after a specific higher capacity of WF the operation cost increased due to wind spillage cost. For the future work, customers can be given a degree of freedom to choose their favorite DR aggregator which leads to a competition among DR aggregators.

Moreover, a more detailed modeling for load reduction can be performed with considering ramp rate constraint of load reduction as a future work. Another future work can be considering the DR uncertainty within the model.

Chapter 4

4 Real-Time Scheduling of Demand Response Options Considering the Volatility of Wind Power Generation

In this chapter, a new methodology to unleash the potential of demand response (DR) in real-time is presented. Customers may tend to apply their DR potential in the real-time market in addition to their scheduled potential in the day-ahead stage. Thus, the proposed method facilitates balancing the real-time market via DR aggregators (DRAs). It can be vital once the stochastic variables of the network such as production of wind power generators (WPG) do not follow the forecasted production in real-time and have some distortions.

Two-stage stochastic programming is employed to schedule some DR options in both day-ahead and real-time markets. DR options in real-time are scheduled based on possible scenarios that reflect the behaviors of wind power generation and are generated through Monte-Carlo simulation method. The merits of the method are demonstrated in a 6-bus case study, which shows a reduction in total operation cost.

4.1 State-of-the-Art and Aims

With the deployment of demand response (DR) in distribution systems, the importance of making the best strategy to take full advantage of demand-side management is well acknowledged [106]. There are several programs for DR either in communication facilities like AutoDR, transactive controllers [169] or in different strategies like emergency DR program (EDRP) and time-of-use (ToU) pricing scheme [86], [93], [170] which should be applied in electricity markets to schedule and optimize the DR usage.

Meanwhile, customers recently play a key role in the market, and this issue should be considered by regulators and policy makers. In other words, the customers have been turned into active players from passive ones [171]. Accordingly, a new player has been introduced in the market called DR aggregator (DRA) in order to be placed as an interface among ISO and customers [162]. DRAs can be active in connection with customers in order to highly benefit from DR implementation either in the wholesale market or retail market.

In terms of wholesale market, the benefit of DRA is maximized for DR trading among ISO and customers in [7]. In [172], the day-ahead and intra-day markets have been considered for DR management by flexibility market operator.

In [173] a model has been proposed to find the best bus for DRA and optimize DR to prevent line congestion in the day-ahead market. All above-mentioned papers have been focused on day-ahead market not real-time one.

Some articles have discussed DR issues in the balancing market. For example, in [174], DR bids are optimized in real-time balancing markets based on supply offers. The model developed by [175] tried to reduce the line congestion and operation cost by DR participation of cooling and heating systems in the real-time retail market. In [176], residential DR in the real-time market has been taken into account in order to schedule the consumption profile based on the price signal. These papers fail to consider DRAs in their model.

Some other investigations have considered DRAs in the real-time market. In [177], DR has been scheduled based on new real-time market dynamic prices for selling energy stored in storage from one aggregator to another in a competitive way. Moreover, references [114], [178] have worked on scheduling DR in the real-time market based on real-time pricing with DRAs. All these papers have not taken into account the unexpected events like the variability of production of wind power generators (WPGs) in real-time markets for DR scheduling.

Stochastic behavior of WPG has been taken into account in our previous work [178] to schedule DR in aggregated-based DR and in day-ahead market, we only used the potential customers in the day-ahead market and not in real time. Similarly, some studies have considered real-time market beside the day-ahead market.

For example, reference [179] aims also to maximize DRA profit while considering customers' issues as well as day-ahead and real-time market clearing in the wholesale market. Definition of the volume of electricity purchased from the day-ahead market, as well as aggregator-based DR quantity has been conducted in [180] in a real-time trading strategy. Nevertheless, DR scheduling in the real-time market is not the aim of these papers.

Thus, there is no study in which, through the unpredicted potential of customers for DR participation in real-time, DRAs are able to optimize DR in the real-time market considering a variation of wind power generation as a stochastic factor in real-time.

In this chapter, it is considered both DRAs and customers as active players in the market. DRAs schedule the DR options involving LC/LS/LR and offer DR prices to customers for participation in the day-ahead market. Meanwhile, the customers may want to reduce or shift more loads in the real-time if an incentive is proposed by DRAs. For example, in the real-time market, customers are able to turn some more lights off or postpone the electric vehicle and washing machine usages, which all were supposed to be consumed according to the day-ahead scheduling.

This strategy is highly desired when some unpredicted events take place in the real-time, and the DRA can cope with the uncertainties. For example, when the wind power generation in real-time is different from the forecasted one or the market price does not live up the expectations or even, customers are able to help avoid any unbalances in the power or remarkable economic loss.

In this chapter, wind power generation is a stochastic variable modeled based on scenario generation using Monte-Carlo Simulation (MCS) method. Thus, wind generation in real-time has been taken into account. Based on these scenarios, new possible DR offers are decided in the real-time market with the new DR capabilities provided by customers.

A two-stage stochastic programming is applied to model the proposed strategy where in the first stage, DRA is scheduled in day-ahead market, and customers and DRAs are scheduled in second stage for new DR potential addition in real-time based on offered incentives and possible scenarios for wind generation. The contributions of this work are briefly summarized as follows:

- Considering unpredicted potential of customers for DR participation in real-time markets.
- Employment of customers' potential for DR participation in the real-time market caused by unpredicted events in addition to their pre-defined potential in the day-ahead market.
- Offering the DR prices (incentives) to encourage customers for involving their extra DR potentials in the real-time market.
- DR quantity optimization in the real-time market through DRAs while considering the volatility of wind power generation as a stochastic factor in real time.

The rest of the chapter is organized as follows. Section 4.2 introduces the DR offers and the way of DRA price bidding. Likewise, scenario generation method and uncertainty handling are illuminated. Section 4.3 presents the formulation of the proposed two-stage stochastic formulation in form of a mixed-integer linear program (MILP). Numerical results and case study are brought in Section 4.4 and finally section 4.5 provides some concluding remarks.

4.2 Problem Statement

One of the key parts of the problem is dealing with the unexpected events in the real time. The way how to model and perform real-time events has the direct impact on the efficiency of this work. The details of the proposed mechanism for modeling the behavior of wind power production in the real-time market are outlined in this section.

Moreover, the problem needs a market strategy to run the day-ahead market while having a look at the real-time market in order to fulfill our requirements. Hence, a pre-emptive market is introduced in this section. Likewise, suitable demand-side management is a complementary stage to reach the best strategy. Therefore, DR options utilized based on the market structure and the proper framework for DRA as well as the method of price bidding for them are explained in this section as well.

4.2.1 Stochastic Modeling

The behavior of wind power production in real time which is stochastic due to the variation of wind speed can be modeled and presented by different scenarios extracted from MSC. To this end, it is needed to produce suitable probabilistic distribution function (PDF) for wind speed. The most suitable PDF for wind speed is the Rayleigh distribution [181].

$$f(v) = \left(\frac{2v}{c^2}\right) \times e^{-\left(\frac{v}{c}\right)^2} \tag{4.1}$$

where c is a parameter, which is called the scale index and determines the shape of $f(v)$; v is the wind speed in (m/s). Through historical data processing, some parameters of forming the probability distribution function (PDF) should be calculated. In this chapter, scale index is obtained from the following acceptable approximation according to [182]:

$$c \approx 1.128 \times v_{mean} \tag{4.2}$$

where v_{mean} is the hourly average forecasted wind speed obtained from a time series. Likewise, generated electric power in the WPG is in associated with the wind speed as the following equation present [183]:

$$p_w = \begin{cases} 0, & v < v_{ci} \cup v_{co} \le v \\ P_r \times \dfrac{(v - v_{ci})}{(v_r - v_{ci})}, & v_{ci} \le v \le v_r \\ P_r, & v_r \le v \le v_{co} \end{cases} \tag{4.3}$$

where v_{ci}, v_{co}, v_r, and P_r are cut-in, cut-out, rated wind speeds and rated power output of WT, respectively.

4.2.2 Scenario Generation

In this section, several scenarios for power generation of wind turbines are generated based on MCS. Using the constructed Rayleigh function, several scenarios that show the behavior of WPG in real-time are generated. The procedure of scenario generation is outlined in Figure 4.1.

Accordingly, having some given and historical data of wind speed value, the mean value is obtained for a specific time period to get the parameters of Rayleigh probability distribution function. Using the cumulative function (CDF) of the obtained Rayleigh function, scenario generation process is conducted. A uniform random variable is fitted to the CDF to get the relative wind speed following by wind power production.

This procedure is repeated until the number of desired scenarios which have the same probability generated. Finally, applying forward reduction method the numbers of scenarios are reduced with different probability to cope with the computational burden. Therefore, in this work ten thousand scenarios are generated for each time step and as we have 24 time steps, the total number of scenarios is 240,000. Applying the above-mentioned reduction procedure; the most important 10 scenarios are remained to study.

4.2.3 Market Structure

A pre-emptive market scheme is run by ISO in this chapter to solve the proposed model based on Figure 4.2 [184]. This scheme is able to confront the renewable generation uncertainty by providing enough flexibility in real-time via day-ahead energy and reserve dispatch. Indeed, day-ahead economic dispatch decisions are considered for real-time operation via various scenarios that include different possible occurrences in the real-time market.

Each Generation company (GENCO) transmits its offers for energy as well as upward and downward reserve capacities to the ISO. Likewise, the DR offers from DR aggregators (DRAs) are sent to ISO and DR scheduling for each hour is sent back to DRAs after market settlement. To solve this short-term management problem, a stochastic two-stage model is employed.

The decisions regarding the first stage of the problem are DR scheduling for aggregators along with energy and reserve of GENCOs at each scheduling period which all are in associated with the day-ahead market. Furthermore, decisions obtained from the second stage of the problem are in connection with the scenarios realization involving the reserve deployment, wind spillage, and real-time DR decisions.

4.2.4 Demand Response Options

It is possible to design a DRA aiming at certain customers group [185], although DRA, here, is assumed as a general and comprehensive aggregator for all customers to reduce any extra correspondence among customers and DRA. Load reduction strategies utilized in this chapter are LC, LR, and LS which are expressed in the following section.

4.2.4.1 Day-Ahead DR Decisions

For the day-ahead DR decisions, three load reduction strategies are considered. In LC option, a customer reduces its consumption without any shifting to other hours. For example, a residential customer can turn-off the TV, or a commercial building can reduce its unnecessary consumptions [7]. The LC contract includes some offers named k that a certain price is dedicated to each one based on the agreement between ISO and DRA named $DR_{tnk}^{Cost,LC}$.

The LC contracts also have a limitation for the amount of load curtailment according to equation (4.5) where u_{tnk}^{LC} is the binary variable to express whether any LC offer is selected.The exact amount of load curtailment related to LC, DRK_{tnk}^{LC}, for DRA is obtained in node n and its total cost achieved through equation (4.4). Meanwhile, equation (4.6) represents the starting time of the offer with $y_{tnk}^{LC} = 1$ and terminating time $z_{tnk}^{LC} = 1$.

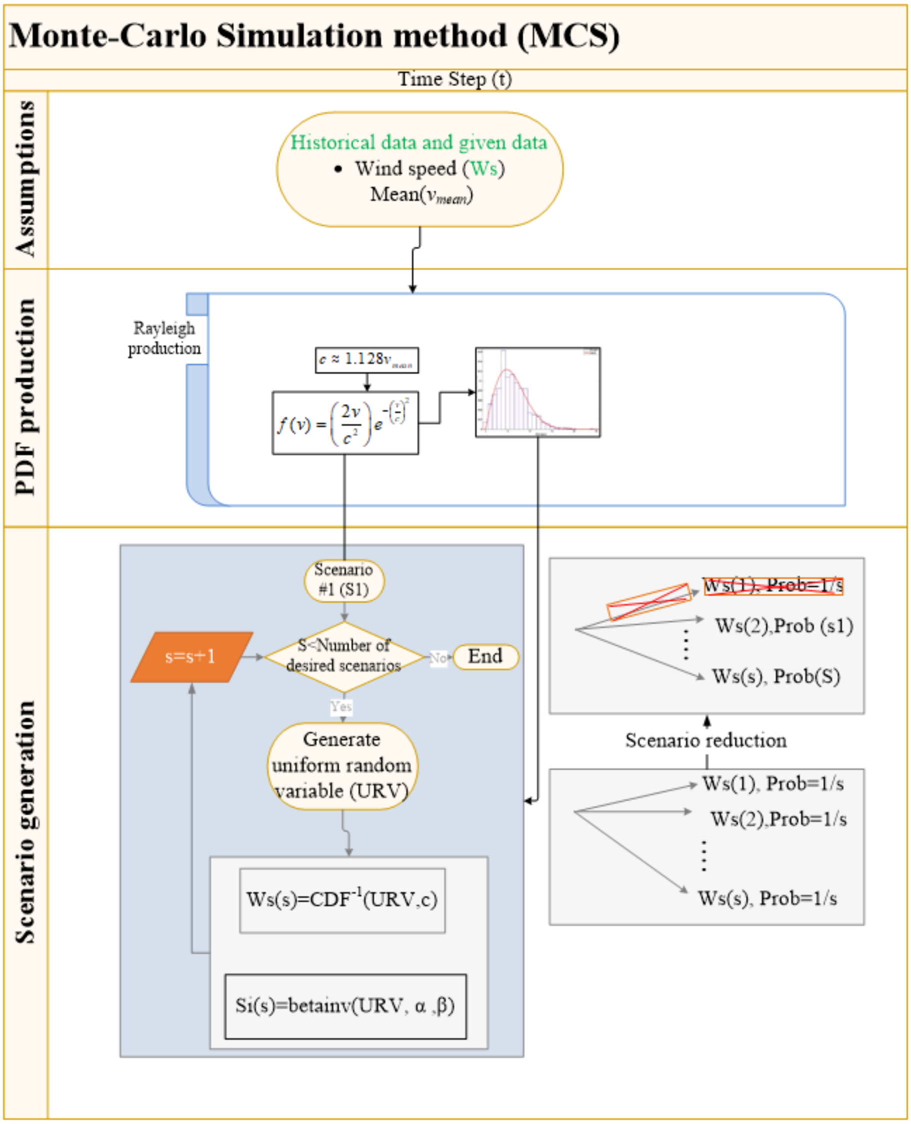


Figure 4.1 The framework of scenario generation for WPG.

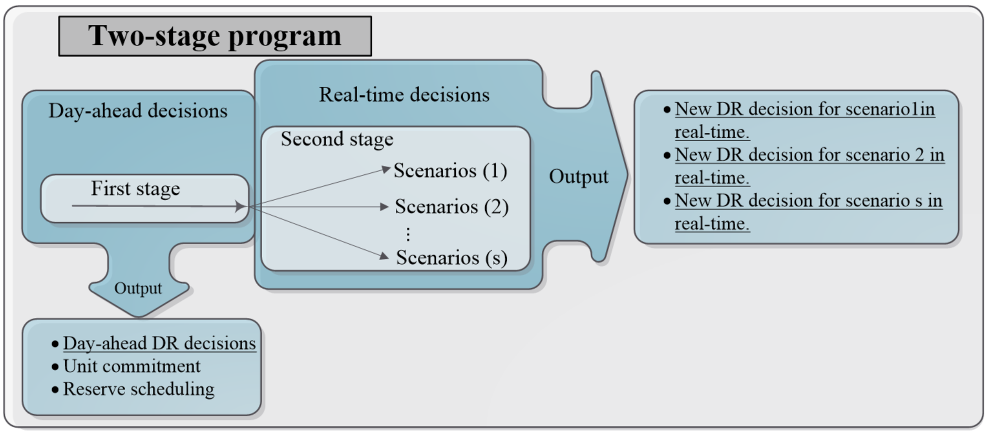


Figure 4.2. Proposed model framework.

Equation (4.7) is to prevent any coincidence in starting and terminating of DR programs. The duration of load reduction process is limited by equations (4.8) – (4.9), and the maximum amount of load curtailment at each day is given in equation (4.10). For LS, all equations of LC will be repeated, and three other equations are needed shifting and recovery of curtailed loads which are introduced in equations (4.11) – (4.13).

According to equation (4.11), the volume of LR, DRK_{tnk}^{LC}, has a special margin determined in the contract. Furthermore, as equation (4.13) states, the summation of LS and LR quantity has to be equal in a day. Meanwhile, according to equation (4.12) the LR and LS should not happen simultaneously.

$$CDR_{tn}^{\hat{X}} = \sum_{k \in KD} DRK_{tnk}^{\hat{X}} \times DR_{tnk}^{Cost,\hat{X}} \tag{4.4}$$

$$DRK_{tnk}^{Min,\hat{X}} \times u_{tnk}^{\hat{X}} \leq DRK_{tnk}^{\hat{X}} \leq DRK_{tnk}^{Max,\hat{X}} \times u_{tnk}^{\hat{X}} \tag{4.5}$$

$$u_{tnk}^{\hat{X}} - u_{t-1nk}^{\hat{X}} = y_{tnk}^{\hat{X}} - z_{tnk}^{\hat{X}} \tag{4.6}$$

$$y_{tnk}^{\hat{X}} + z_{tnk}^{\hat{X}} \leq 1 \tag{4.7}$$

$$\sum_{t}^{t+LCD_{nk}^{\max,\hat{X}}-1} z_{tnk}^{\hat{X}} \geq y_{tnk}^{\hat{X}} \tag{4.8}$$

$$\sum_{t}^{t+LCD_{nk}^{\min}-1} u_{tnk}^{\hat{X}} \geq LCD_{nk}^{\hat{X},\min}(u_{tnk}^{\hat{X}} - u_{t-1nk}^{\hat{X}}) \tag{4.9}$$

$$\sum_{t} y_{tnk}^{\hat{X}} \leq MC_{nk}^{\hat{X}} \tag{4.10}$$

$$DRK_{tnk}^{LR} \leq DRK_{tnk}^{\max,LR} \times u_{tnk}^{LR} \tag{4.11}$$

$$u_{tnk}^{LR} + u_{tnk}^{LS} \leq 1 \tag{4.12}$$

$$\sum_{t \in TR} DRK_{tnk}^{LR} = \sum_{t \in TS} DRK_{tnk}^{LS} \tag{4.13}$$

4.2.4.2 Real-Time DR Decisions

For real-time DR decision, according to the possible events which are determined in the scenarios, new decisions for DR which will be implemented in real-time will be made. DRAs provide this opportunity for the customer to participate even in the real-time market in order to use any possible potential of customers' consumption to shift or curtail which was not clarified in the day-ahead stage.

Therefore, customers utilize this opportunity to propose any new possible potential for participation in DR within real-time. Having performed this strategy leads to not only profit for customers to sell DR with a higher price in real-time but also provide less expensive power balance for ISO followed by a profit for DRAs. The equations of real-time DR would be as follows:

$$CDRs_{tns}^{\hat{X}} = \sum_{k \in KD} DRKs_{tnks}^{\hat{X}} \times DR_{tnk}^{Cost,\hat{X}} \tag{4.14}$$

$$DRKs_{tnks}^{Min,\hat{X}} \times us_{tnks}^{\hat{X}} \le DRKs_{tnks}^{\hat{X}} \le DRKs_{tnks}^{Max,\hat{X}} \times us_{tnks}^{\hat{X}} \tag{4.15}$$

$$us_{tnks}^{\hat{X}} - us_{t-1nks}^{\hat{X}} = ys_{tnks}^{\hat{X}} - zs_{tnks}^{\hat{X}} \tag{4.16}$$

$$ys_{tnks}^{\hat{X}} + zs_{tnk}^{\hat{X}} \le 1 \tag{4.17}$$

$$\sum_{t}^{t+LCD_{nk}^{\max,\hat{X}}-1} zs_{tnks}^{\hat{X}} \ge ys_{tnks}^{\hat{X}} \tag{4.18}$$

$$\sum_{t}^{t+LCD_{nk}^{\min}-1} us_{tnks}^{\hat{X}} \ge LCDs_{nk}^{\hat{X},\min} \times (us_{tnks}^{\hat{X}} - us_{t-1nks}^{\hat{X}}) \tag{4.19}$$

$$\sum_{t} y_{tnks}^{\hat{X}} \le MCs_{nks}^{\hat{X}} \tag{4.20}$$

$$DRK_{tnks}^{LR} \le DRKs_{tnk}^{\max,LR} \times us_{tnks}^{LR} \tag{4.21}$$

$$us_{tnks}^{LR} + us_{tnks}^{LS} \le 1 \tag{4.22}$$

$$\sum_{t \in TR} DRKs_{tnks}^{LR} = \sum_{t \in TS} DRKs_{tnks}^{LS} \tag{4.23}$$

Equations (4.14) – (4.23) represent the real-time contract scheme and options for DR among DRAs and customers. The framework of DR options is similar to the day-ahead market, though the DR threshold and price in real-time would be different.

4.2.4.3 DR Price Bidding Scheme

In fact, the DR cost is non-linear since both the price and DR quantity are variables. To prevent trapping in a local optimal point in solving nonconvex problems which leads to high financial losses, a method to achieve a linear problem is applied. To this end, we employ a stepwise price curve method that is precise enough in linearization, and a customer reacts to various prices in a stepwise approach. Therefore, each step has a fix price, and the reduced volume would be a decision variable with a certain range. In other words, DR prices/incentives are set as several fix values and different blocks are established based on these fixed values. Each block has a range of DR quantity assigned to one of those fix DR prices/incentives. The model selects one or several blocks for customers based on relative prices/incentives. At each block DR quantity can be scheduled within the relative limitation.

Thoroughly, the model starts selecting the blocks/steps from lower prices/incentives to higher ones and the number of selected blocks/steps and DR quantity are based on their cost-efficiency. It means customers tend to select blocks and the relative DR quantities from the lower block to higher one according to the benefits it may bring them. The stepwise function is depicted in Figure 4.3. It is noticed that the DR price bidding in the day-ahead market by DRA is usually less than that in the real-time market. Because in real-time market, customers expect a higher price for their DR offers and the market price would be higher as well.

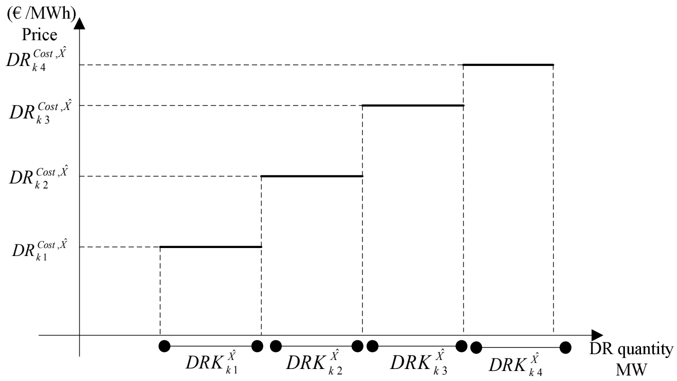


Figure 4.3. DR price bidding for day-ahead and real-time market

4.3 Two-Stage Stochastic Programming

To solve the proposed methodology, a two-stage stochastic programming is utilized which is the fittest model for this problem. The objective function, equation (4.24) aims to minimize the total operation cost with different relative constraints as a MILP problem. The relative constraints are listed in equations (4.25) – (4.36). The first and second lines of equation (4.24) correspond to the first stage that involves units' power generation cost, start-up and shut-down costs for thermal units, upward and downward reserve capacities cost of units along with demand response options cost.

In equation (4.24), the third and fourth lines are in connection with the second stage (real-time decisions) that involves real-time total DR cost for all scenarios as well as energy cost, upward and downward reserve, and wind spillage cost in all scenarios; equations (4.25)–(4.36) represent first-stage constraints; units' capacity limitations are brought in equations (4.25) – (4.26); day-ahead balance equality is given by equation (4.27).

Reserve restrictions of units are given by equations (4.28) – (4.29); equations (4.30) – (4.31) indicate the ramp-up and ramp-down constraints of thermal units; the constraints regarding the start-up/shut-down costs of thermal units are presented in equations (4.32) – (4.33); DC load flow is brought in equation (4.34), and the capacity constraint of transmission line is given in equation (4.35).

Equation (4.36) represents the limitation of scheduled power generation of WPG that ought to be lower than the forecasted amount of wind power. Meanwhile, equations (4.4) – (4.13) are employed to calculate DR costs in day-ahead market and equations (4.14) – (4.23) are utilized to obtain the DR cost in the real-time market.

The second-stage constraints are given by equations (4.36) – (4.42); the power balancing equation for the real-time market is brought in (4.37). Equations (4.38) – (4.39) indicates DC power flow constrain for real-time are given by wind-spillage should be no greater than the available output in each scenario, which is shown in equation (4.40). Limitations of upward and downward regulation in each scenario are provided by equations (4.41) – (4.42).

Moreover, the constraint of scheduled DR in scenarios is brought in equation (4.43). Accordingly, there is a relationship among scheduled DR in day-ahead and real-time market implied DR in scenarios cannot be more than scheduled DR in the day-ahead market. In objective function, equation (4.24), the day-ahead decision variables are P_{tg}^{gen}, SUC_{tg}^{gen}, R_{tg}^{up}, R_{tg}^{down}, CDR_{tn}^{LC}, CDR_{tn}^{LS}, and the real-time decision variables include. These variables are defined through minimizing equation (4.24) by considering following constraints:

$$
\begin{aligned}
&Minimize \sum_{t\in NT}\left\{\sum_{g\in NG}(C_{tg}^{gen}\times P_{tg}^{gen}+SUC_{tg}^{gen}+C_{tg}^{up}\times R_{tg}^{up}+C_{tg}^{down}\times R_{tg}^{down})\right.\\
&+\sum_{n\in NN}(CDR_{tn}^{LC}+CDR_{tn}^{LS})\\
&+\sum_{s\in S}\pi_s\left[\sum_{g\in NG}(Cs_{tgs}^{up}\times Rs_{tgs}^{up}+Cs_{tgs}^{down}\times Rs_{tgs}^{down})\right.\\
&\left.\left.+\sum_{n\in NN}(Cs_{tns}^{spill}\times W_{tns}^{spill}+Cs_{tns}^{voll}\times Ls_{tns}^{shed})+\sum_{n\in NN}(CDRs_{tns}^{LC}+CDRs_{tns}^{LS})\right]\right\}
\end{aligned} \tag{4.24}
$$

$$P_{tg}^{gen}+R_{tg}^{up}\le P_g^{\max}\times u_{tg}^{gen} \tag{4.25}$$

$$P_{tg}^{gen}-R_{tg}^{down}\ge P_g^{\min}\times u_{tg}^{gen} \tag{4.26}$$

$$\sum_{g\in NG}p_{tg}^{gen}+W_{tn}^{sch}+\sum_{k\in KD}(DRK_{tnk}^{LC}+DRK_{tnk}^{LS}-DRK_{tnk}^{LR})=LD_{tn}+\sum_{l\in NL}pf_{tl} \tag{4.27}$$

$$0\le R_{tg}^{up}\le R_g^{\max,up} \tag{4.28}$$

$$0\le R_{tg}^{down}\le R_g^{\max,down} \tag{4.29}$$

$$P_{t-1g}^{gen}-P_{tg}^{gen}\le Rmp_g^{up} \tag{4.30}$$

$$P_{tg}^{gen}-P_{t-1g}^{gen}\le Rmp_g^{down} \tag{4.31}$$

$$SUC_{tg}^{gen}\ge C_g^{strt.up}(u_{tg}^{gen}-u_{t-1g}^{gen}) \tag{4.32}$$

$$SUC_{tg}^{gen}\ge C_g^{sht.dwn}\times(u_{t-1g}^{gen}-u_{tg}^{gen}) \tag{4.33}$$

$$pf_{tl}=\sum_{n\in NN}\frac{1}{X_{nl}}\times(\theta_{nl}^{1}-\theta_{nl}^{0}),\quad -2\pi\le\theta_{nl}\le 2\pi \tag{4.34}$$

$$pf_l^{\min}\le pf_{tl}\le pf_l^{\max} \tag{4.35}$$

$$0\le W_{tn}^{sch}\le W_{tn}^{\exp} \tag{4.36}$$

$$
\begin{aligned}
&\sum_{g\in NG}(Rs_{tgs}^{up}-Rs_{tgs}^{down})+W_{tns}^{scen}-W_{tn}^{sch}-W_{tns}^{spill}+\sum_{k\in KD}(DRKs_{tnks}^{LC}+DRKs_{tnks}^{LS}-DRKs_{tnks}^{LR})=\\
&-\sum_{l\in NL}(pfs_{tls}-pf_{tl})
\end{aligned} \tag{4.37}
$$

$$pfs_{tls}=\sum_{n\in NN}\frac{1}{X_{nl}}\times(\theta_{nls}^{1}-\theta_{nls}^{0}),\quad -2\pi\le\theta_{nls}\le 2\pi \tag{4.38}$$

$$pf_l^{\min}\le pfs_{tls}\le pf_l^{\max} \tag{4.39}$$

$$0\le W_{tns}^{spill}\le W_{tns}^{scen} \tag{4.40}$$

$$0\le Rs_{tgs}^{up}\le R_{tg}^{up} \tag{4.41}$$

$$0 \le Rs_{tgs}^{down} \le R_{tg}^{down} \tag{4.42}$$

$$DRKs_{tnks}^{\hat{X}} \le DRK_{tnk}^{\hat{X}} \tag{4.43}$$

4.4 Numerical Studies

To implement the proposed model in a network and assess the merits of the model two networks are employed including a 6-bus IEEE test system and RTS-96. The 6-bus system is demonstrated in Figure 4.4. Thermal generation units' data, line data and DR prices are presented in Table 4.1, Table 4.2, and Table 4.3, respectively. In Table 4.3, DR prices for different options including LC, LS and different offers (5 offers, $k1$ to $k5$) in the day-ahead market and the real-time market are given. It is assumed that DR prices for LC and LS are the same.

Likewise, there are three DRAs. Each DR option in different DRAs has a boundary, which DR can be scheduled between these boundaries. It is noteworthy that LC and LS can be implemented in hours between 10 – 16 and 10 – 18, respectively. The maximum and minimum of DR contracts for all 5 offers are the same and for DRA #1 - #3, for LC, LS and in the day-ahead market.

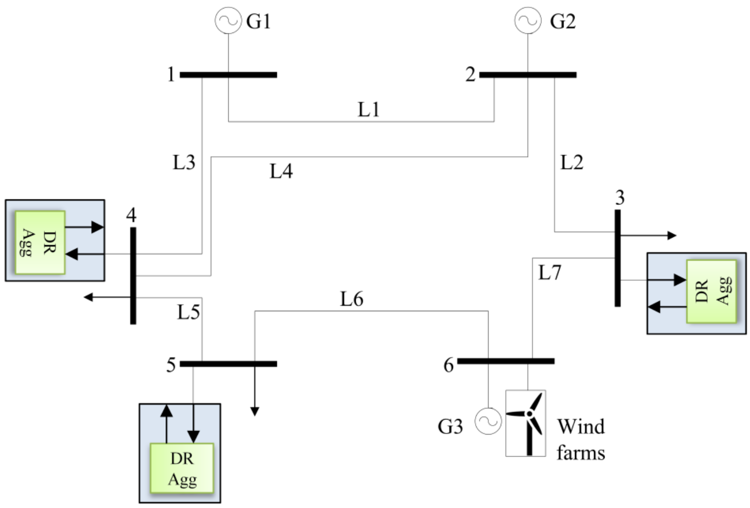


Figure 4.4. The diagram of 6-bus network.

Table 4.1 Units' Data.

#	Bus	Generation Cost (€/kWh)	Minimum capacity (kW)	Maximum capacity (kW)	Start-up cost (€/kWh)	Shut-down cost (€/kWh)	Ramp rate (kWh)	Min on-time (h)	Min off-time (h)	Reserve-up limit (kWh)	Reserve down limit (kWh)	Reserve up cost	Reserve down cost
G1	1	13.50	100	220	100	50	100	4	4	110	110	15	10
G2	2	40.00	10	100	200	100	60	3	2	50	50	45	35
G3	6	17.70	10	40	0	0	30	1	1	15	15	20	15

Table 4.2 Transmission line data.

Line	X	Capacity
L1	0.170	200
L2	0.037	100
L3	0.258	100
L4	0.197	100
L5	0.037	100
L6	0.140	100
L7	0.018	100

According to equations (4.44) – (4.45), the maximum of DR contract for LC and LS is a coefficient of load demand plus a parameter γ in the special bus that DRA is placed; $\alpha = 0.01$, and $\gamma = 0$ are used in this section. Moreover, the minimum of DR contract is the same coefficient of the load in the bus minus a parameter $\beta = 0.58$.

It should be noted that LC at periods 17 and 18 are not scheduled, while equations (4.44) – (4.45) are taken into account for LS at these hours. Limitation of DR contracts in the real-time market has the same equation like those in the day-ahead market, yet the parameters γ and β can take different values.

Here β and γ are 0.48 and -0.01, respectively. Since in real-time the potential of customers to participate in DR is less, the boundary of DR contract is narrower than the day-ahead market. The general relationship among DR boundary in the day-ahead and real-time markets is like Figure 4.5.

$$DRK_{tnk}^{Max,\hat{X}} = \alpha \times LD_{tn} + \gamma, \quad (\hat{X} \in LC, t \in 10-16 \cap \hat{X} \in LS, t \in 10-18), n \in 3,4,5. \tag{4.44}$$

$$DRK_{tnk}^{Min,\hat{X}} = \alpha \times LD_{tn} - \beta, \quad (\hat{X} \in LC, t \in 10-16 \cap \hat{X} \in LS, t \in 10-18), n \in 3,4,5. \tag{4.45}$$

$DRK_{tnk}^{max,LR}$ for LR option is considered 2MW in day-ahead DR scheduling and 1.5MW in real-time DR scheduling. The CPLEX12 solver in GAMS [186] is applied to solve the problem utilizing a Intel processor core i7, cache 2.7GHz, and random-access memory (RAM) 8GB. It takes around 1 second to solve the problem. The CPLEX12 optimizer is designed to solve large and difficult linear or mixed integer programming (MIP) problems quickly.

For problems with integer variables, CPLEX uses branch and cut algorithm that solves a series of linear problems and sub-problems, since an MIP produces many sub-problems following by intensive computation. The proposed model is an MIP, and CPLEX12 optimizer with branch and cut algorithm solves the problem. Based on GAMS solution report, the problem is feasible.

In this chapter, the differences among scenarios after running DR options for them are mostly compared with each other as case 2. Though, case 1 includes the same method without running DR options in the real-time market for scenarios and the DR options run just in the day-ahead market.

Finally, a larger network, RTS-96, is applied as the last case study to compare solving status among 6-bus system and 72-bus test system. All cases are presented in Table 4.4. Through the proposed method to generate scenarios for WPGs, ten scenarios are generated. All ten scenarios along with forecasted wind power production are demonstrated in Figure 4.6.

Table 4.3 DR prices for 5 offers and two options.

Market		K1 (€/MWh)	K2 (€/MWh)	K3 (€/MWh)	K4 (€/MWh)	K5 (€/MWh)
Day-Ahead	**LC & LS Price**	10	11	12	13	14
Real-Time	**DR-Price1**	6	7	8	9	10
	DR-Price2	8	9	10	11	12
	DR-Price3 (Case 2)	11	12	13	14	15
	DR-Price4	14	15	16	17	18
	DR-Price5	20	21	22	23	24
	DR-Price6	24	25	26	27	28
	DR-Price7	30	31	32	33	34
	DR-Price8	35	36	37	38	39

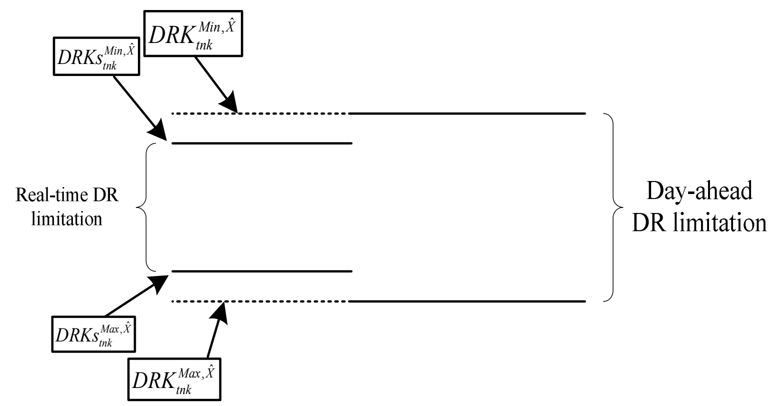


Figure 4.5. The relationship between the limitation of DR quantity in the day-ahead and real-time markets.

Table 4.4 Case studies.

Cases	Description	Output
Case1	6-bus system, DR employment just in day-ahead market.	DR quantity just in day-ahead market.
Case2	6-bus system, DR employment in both day-ahead market and real-time market.	DR quantity in day-ahead market and real-time market with 10 scenarios.
Case3	72-bus system, DR employment in both day-ahead market and real-time market.	DR quantity in day-ahead market and real-time market with 10 scenarios.

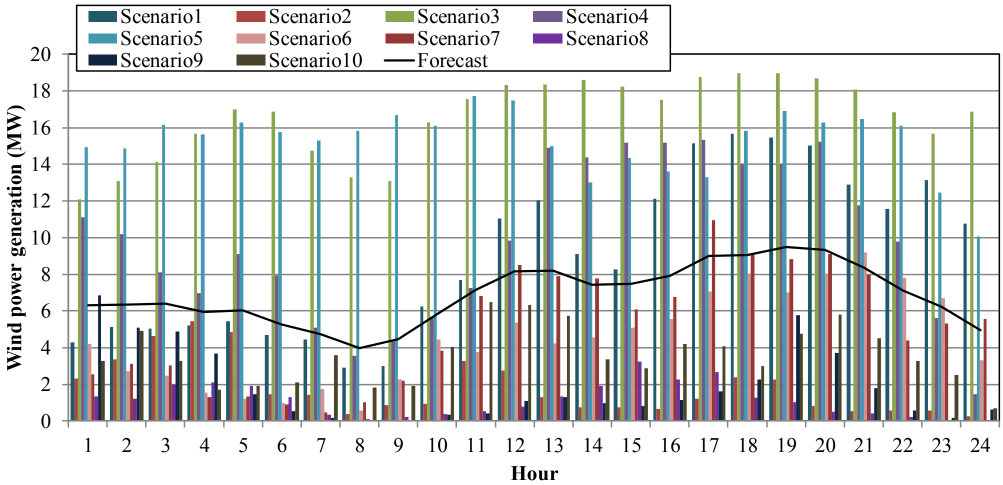


Figure 4.6. Forecasted wind power generation and all scenarios extracted via the model.

Note that in this chapter, 3 DRAs for cases 1 and case 2 and 30 DRAs for case 3 are taken into account. Moreover, the problem considers network constraints as DC load flow. As can be seen, scenario 2 has the minimum wind power production in a day. For example, the maximum production for scenario 2 is 5MW out of 20MW, and scenario 3 has the maximum wind power production in a way the maximum production is 19MW for this scenario. The range of power production in scenarios 4 and 5 are between scenarios 2 and 3.

Meanwhile, in Figure 4.7, the result of real-time DR scheduling for these four selected scenarios along with day-ahead DR scheduling are presented. The impact of running this model on load for these scenarios can be seen in Figure 4.7. Moreover, the load profile after running the proposed method in case 2 for the day-ahead market is illustrated. The results of load after running DR in the day-ahead market for case 1 without running DR options in scenarios and real-time market are outlined in Figure 4.7.

For scenario 2, the load reduction is higher in peak hours, since it has the minimum wind power production compared with the forecasted one. Therefore, to compensate this shortage of production, DR options are applied to reduce the load, though the loads are recovered in off-peak hours. As a result, the highest load reduction occurs for scenario 2. On the other hand, less load reduction is observed in scenario 3, since it has the highest wind power production among all these scenarios.

Figure 4.8 demonstrates the amount of reduced load as well as shifted loads for all DR aggregators per scenarios at each time step. Accordingly, the shifted and recovered loads have the negative sign and the reduced loads have the positive one. As a result, the real-time DR decisions for different scenarios are always less than day-ahead DR decisions which means DR for scenarios are related to DR in day-ahead and is scheduled based on what is decided for the day-ahead market. A comparison among the DRAs cost for running DR options in all scenarios is performed in Figure 4.9; in Figure 4.9 a), there is no LC for scenario 3, since in this scenario the highest wind power generation is foreseen. Therefore, there is no need to reduce load, and all loads are served.

Scenario 5 is nearly similar to scenario 3; hence, there is no DR cost for DRA 2 and for two other DRAs, it is too low, 100€ for DRA 3 and 250€ for DRA 1. Although, the DR cost for other scenarios and DRA for running the LC are nearly the same. DR cost, generally, for DRA 1 is lower than two other DRAs because the amount of load which is under control of DRA 1 is lower.

In Figure 4.9 b), LS cost is considered. In all scenarios, LS is applied, yet LS cost is mostly less than LC cost. Generally, the LS cost is around 300€, although LS cost for DRA 3 is around 400€ in scenario 5 and LS cost is 150€ for DRA 1. Moreover, as can be seen in part c) the total DR cost, i.e., the summation of LS and LC cost, is minimum for scenario 3 and 5 which have the highest possible wind power productions. Although the prices for other scenarios are about 900€ for DRA 2 and 3, and 500€ for DRA 1.

Finally, the most interesting part of results regards to Table 4.5. Based on this table, the proposed method has less total operation cost compared with case 1 where there is no DR scheduling for scenarios in real-time. Nevertheless, the day-ahead DR scheduling for case 2 is more.

The reason behind this is why the need for a reserve of units in different scenarios is reduced because of applying a new methodology for DR in real-time, which is less costly than units' reserve. To show the impacts of real-time DR price on the total operation cost and the DR cost, a sensitivity analysis is conducted. To this end, some variable real-time DR prices with lower and higher values than the base case 2 (DR-Price3) are taken into account which are introduced in Table 4.3 in real-time stage.

In Table 4.5, DR prices for case 2 is assigned as DR-Price3. The results are demonstrated in Figure 4.10. In Figure 4.10, eight real-time DR prices are considered to make a comparison among different total operation costs and total DR costs. As can be seen in Figure 4.10, with increasing the DR price, total operation cost always has an incremental trend. This increase occurs from 88,100€ in DR-Price1 to 88,700€ in DR-Price8 which is the highest real-time DR price in this package.

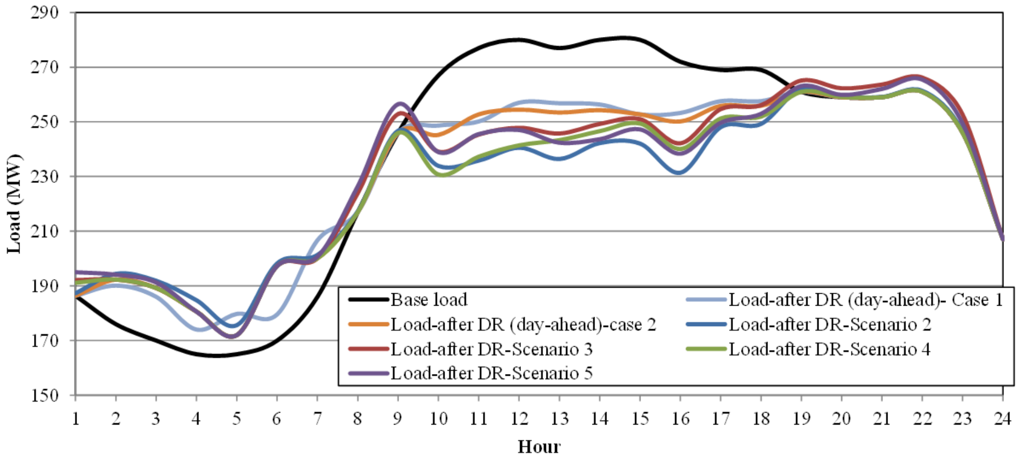


Figure 4.7. Base load and loads after DR in different states.

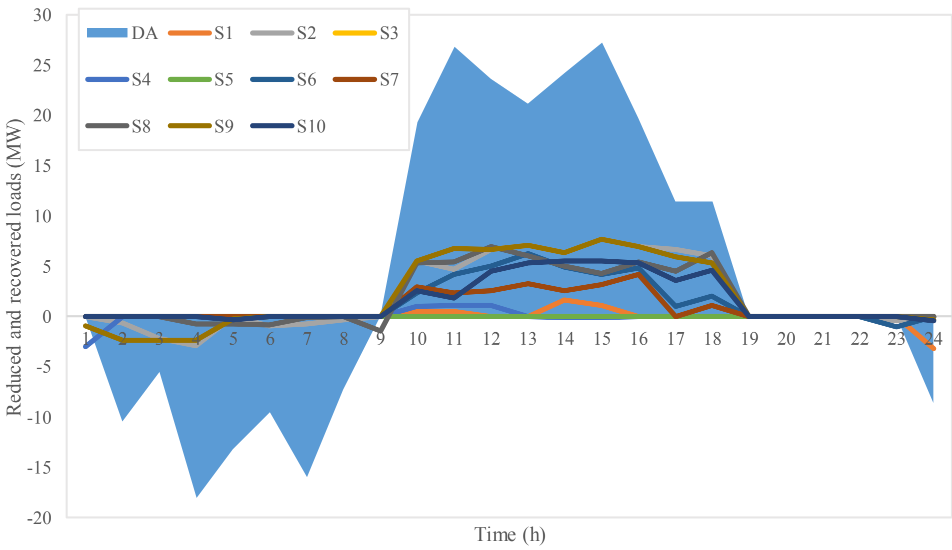


Figure 4.8. the quantity of DR for all three options LC, LS, and LR and all DR aggregators per scenarios and in the day-ahead market.

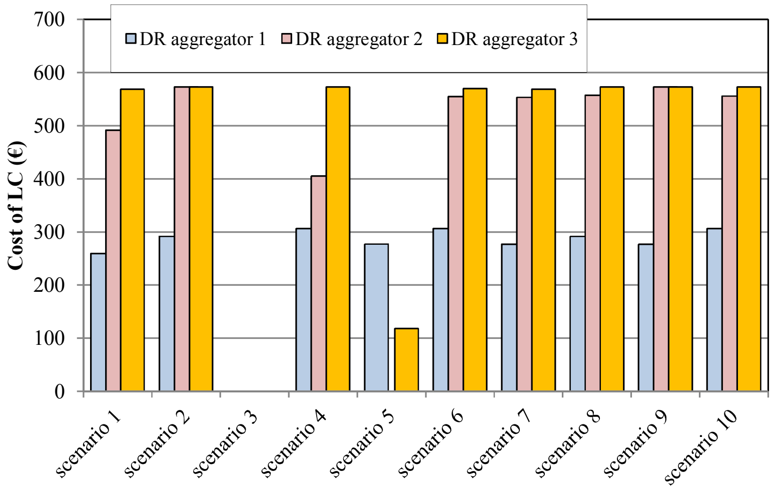
The reason behind this phenomenon is why rising the real-time DR price causes more expense for aggregators. In other words, aggregators have to spend more money to buy DR participation of customers in both real-time and day-ahead market. On the other hand, DR cost has a decrement trend in a way that with increasing the real-time DR price, DR cost is dropped.

Once the DR price is high, DRA tries to buy less DR from customers. Therefore, despite the fact that the DR price is going to increase, the DR cost tends to be lower. This attitude is depicted in Figure 4.11.

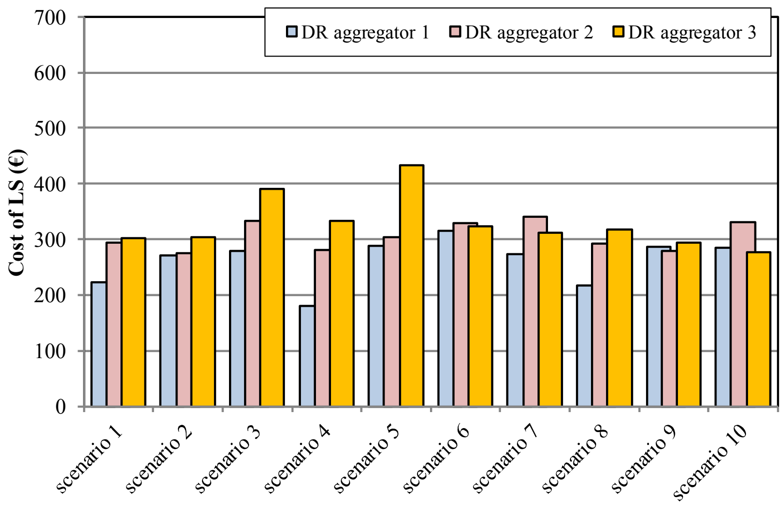
In Figure 4.11, the effect of real-time DR price packages DR-Price4 and DR-Price5 on LC scheduling for scenarios 8 and 9 are compared. According to the figure, for scenario 8 and 9, the LC in DR-Price5 is scheduled always less than DR-Price4 which leads to a lower DR cost.

The proposed model is also implemented in the large-scale network, i.e. IEEE RTS-96, to demonstrate the possibility and applicability of running the model on real networks. Therefore, the results of the model implementation on IEEE RTS-96 with 72 buses are brought in Table 4.6 and compared with 6-bus system.

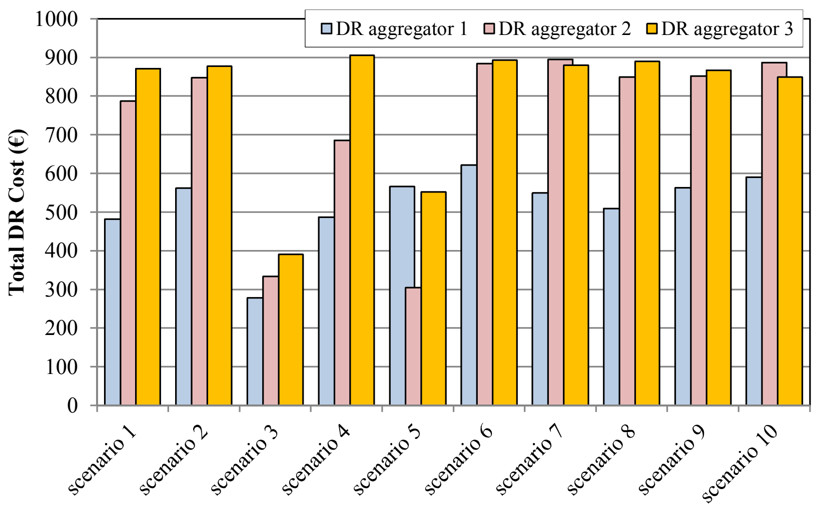
The comparison is conducted between the number of variables, iterations, execution time and total cost as the objective function. Note that we assumed 35 demand response aggregators and 30 wind farms in the new case study. Accordingly, in RTS-94, it just takes more time to solve the model due to higher number of iterations and variables.



a) LC cost for different DRAs in all scenarios



b) LS cost for different DRAs in all scenarios



c) Total DR cost for different DRAs in all scenarios

Figure 4.9. DR cost in different DRAs and different scenarios a) total cost b) LS cost c) LC cost.

Table 4.5 Different costs in all cases

Cases	Total cost (€)	DR cost (€)
Case 1	90,158.04	2,142.350
Case 2	86,054.10	2,336.683

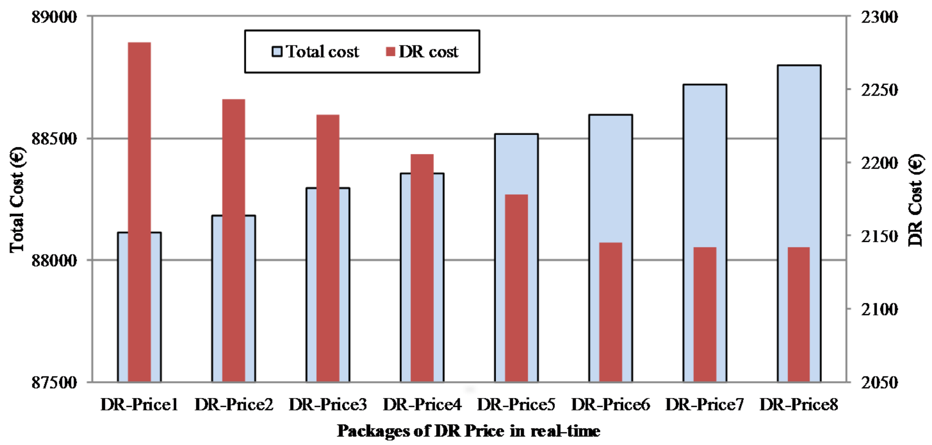


Figure 4.10 Sensitivity analysis for different real-time DR price for total cost and DR cost.

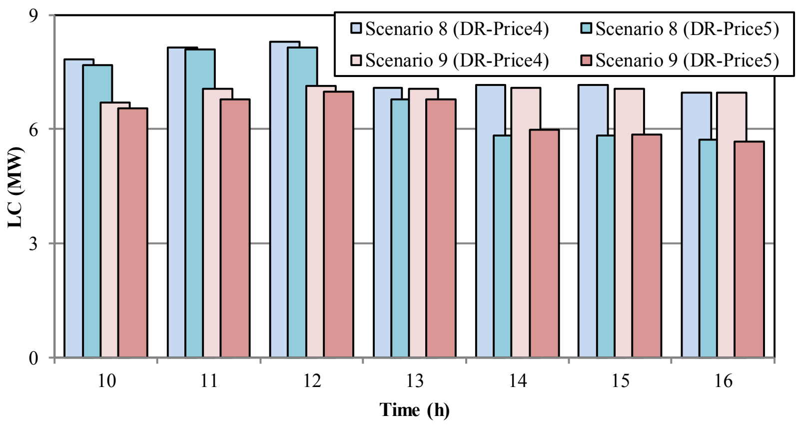


Figure 4.11. Differences of LC scheduling in two scenarios for two DR prices.

Table 4.6 Comparison the results of performing the model on 6-bus system and RTS-96

	6-bus System	RTS-96
Number of Variables	229	872
Number of Iterations	2,598	63,175
Total Cost (objective Function)	89,217.89€	693,751.09€
Execution Time	0.91 Seconds	165.5 Seconds

4.5 Brief Remarks of this Chapter

In this chapter, a two-stage MILP stochastic model was applied to schedule the real-time DR options including LC, LR and LS. Ten scenarios have been generated through the MCS method to show the different possible amount of WPG at each hour. Through this methodology, in addition to day-ahead DR scheduling by coordination of DRAs and customers, DR options in real-time market are scheduled for DRAs based on each scenario that shows shortage or enough wind power production.

Hence, the more wind power is produced in each scenario, the less DR is applied in that scenario. Moreover, this method has lower total operation cost compared to when there is no option for DR scheduling in the real-time market. Considering uncertainty in demand side and DR as well as customers’ comfort are offered as future works.

Chapter 5

5 Stochastic Management of Demand Response Aggregators Considering Customers' Preferences within Distribution Networks

In this chapter, a demand response (DR) trading scheme among end-users and DR aggregators (DRAs) is proposed within the retail market framework. This scheme aims to obtain optimum DR volume to be exchanged while considering both DRAs' and customers' preferences. To this end, a bi-level programming model is formulated. In the upper-level problem, the total operation cost of the distribution system, which consists of DRAs' cost and other electricity trading costs, is minimized.

DR selling for customers is maximized in the lower-level problem based on DR prices. In the upper level, a two-stage problem is modeled to consider day-ahead decisions in the first stage and balancing decisions in the second stage. Furthermore, the intermittent nature of renewable sources generation is handled by scenario generation with Monte-Carlo Simulation (MCS) method. Likewise, all relative distribution network constraints are taken into account considering a linear power flow for radial networks.

The results of the implementation of the proposed model demonstrate the effectiveness of different DR prices and different number of DRAs on hourly DR volume, hourly DR cost and power exchange between the studied network and upstream network.

5.1 State-of-the-Art and Aims

Demand response (DR) trading within retail markets plays a key role to overcome the intermittent nature of huge number of weather-dependent renewable energy sources (RESs) such as photovoltaic systems (PVs) and wind farms (WFs). Hence, a specific scheme and structure should be designed to implement demand-side management in retail markets.

According to [187], there is no established market for DR in Nordic countries, where some pioneer countries in market design, especially reserve market, exist in Finland. However, distribution system operators (DSOs) have the allowance of making direct agreements on DR with customers only in Norway and Denmark.

Moreover, no business model has been designed for demand response aggregators (DRAs) in Nordic countries. For example, Denmark is still in a regulatory discussion phase. Sweden has introduced an actor similar to the so-called balance service provider (BSP) who is able to place bids on the retail market without taking the balance responsibility.

Thus, according to these examples, there is the lack and gap of such structures for DR implementation when considering important and active players like DRAs and customers in the most electricity markets. As a result, some profound and practical studies to make a suitable structure in the retail market are required.

A number of studies have addressed how DR is used by different markets and utilities like DSO and retail market. For example, operation scheduling of microgrids has been studied in [101] via a two-stage stochastic program while considering an ancillary service demand response program (ASDR), and network constraints have been neglected. Nevertheless, there are some works in distribution networks while considering network constraints as linear power flow without DR implementation [188]-[192].

Moreover, DR scheduling has been conducted from DRA's viewpoint in some literature. For example, authors in [7] have applied two DR options including load curtailment and load shifting to maximize DRA profit. A DR trading framework for DRAs has been proposed in [193] in which TOU and reward-based DR program have been applied for trading with the customer. DR option agreements have been employed for DR trading with DR purchasers similar to the wholesale market.

Competitive scheduling for DRAs to sell the pre-stored energy through storage devices has been conducted in [194]. In [161], DRA has been optimized in a two-stage problem that aims to minimize the total operation cost from DSO's viewpoint while considering incentive-based DR programs. All above mentioned papers mainly have been modeled the problem from distribution system viewpoint disregarding customers' preference.

On the other hands, some investigations has been focused on how customers take advantage of their DR capability using household energy management (HEMs) and detail information regarding appliances for end-users [195]-[197]. For instance, in [195], authors have considered a new index called response fatigue in addition to customer satisfaction and electricity trading to minimize the billing cost for one customer.

Time-of-use (TOU) DR has been applied in [196] for customers to optimize dispatch of source-load-storage in a HEMs framework. Likewise, a multi-objective approach has been engaged in [197] to manage flexible loads and minimize not only the electricity bill but also the customers' dissatisfaction. These papers fail to model how likely utilities will be interested in their DR.

There are a few papers which model DR in a bi-level programming model. In [3], [178], DR scheduling from the independent system operator (ISO)'s viewpoint considering two different levels has been performed. In [178], a market scheme has been designed within the wholesale market considering DRAs. The DR quantity for trading between the ISO and the DRA has been optimized in a bi-level program.

In [198], authors have modeled the interaction among retailers and customers to define a real-time price for customers for their DR participation. Some uncertainties like the price has been considered in a stochastic bi-level model to maximize retailers profit while consumers optimize their consumption.

The similar problem has been addressed in [199] via bi-level robust optimization with uncertain coefficients in the objective function. Authors in [179] proposed a bi-level optimization model to optimize DR contracts for DRA while considering customers satisfaction factor. Where in the upper-level problem, DRA profit is maximized; in the lower-level problem, ISO runs a real-time market process to obtain aggregators' bid and optimum power for DRA.

In other research works, such as [200], [201], bi-level modeling has been performed to optimize dynamic tariffs according to which customers participate in a DR program. To this end, retailers in the upper level aim to maximize the profits and customers in the lower level intend to manage their loads based on the price signal and their comfort needs by minimizing the billing cost. These papers have not modeled a comprehensive approach in which DSO, DRAs and customers preferences are addressed and at the same time competitions among DRAs to attract customers DR is modeled.

To obtain the optimum volume of DR trading in a short-term scheduling of the retail market, the operator should minimize the total operation cost in which buying DR by DRA is a part of operation costs. At the same time, customers would like to maximize their DR selling to increase their income, or equivalently, decrease the billing cost. Meanwhile, all network constraints, as well as stochastic variables like PV and WT generation, should be considered to achieve more practical and precise results.

To the best of our knowledge, no study has been conducted to schedule DR volume to trade among DRAs and customers with all above-mentioned features. In this chapter, a bi-level programming model is proposed to optimize DR trading among DRAs and customers in a competitive way and within the retail market. The upper-level problem aims to minimize the operation cost from DSO's or microgrid operator's viewpoint. In this level, DRAs are a part of operation cost for operators to buy DR from customers.

The lower-level problem is to maximize DR selling from customers' viewpoint. In the upper-level problem, a two-stage stochastic program model is used to capture day-ahead market decisions along with real-time market decisions with all network constraints and handle uncertainties of renewable generations.

The uncertainties are modeled by a Monte-Carlo Simulation method and scenario generation. The bi-level problem is turned into a single-level problem with equilibrium constraints by replacing the lower-level problem with its Karush-Kuhn-Tucker (KKT) conditions. The contributions of the work are as follows:

- DR is traded among DRAs and customers in a way that customers can select the proper DRA based on DR prices;
- A business model for obtaining DR quantity is proposed in the retail market. DRAs, within the operator's area, are scheduled to buy DR, while customers' preference to maximize DR selling is considered, simultaneously, in a bi-level model;

- Distribution network constraints as linear power flow are implemented in two-stage stochastic programming in which the intermittent nature of PV and WT power generation is considered, as well.

The rest of the chapter is organized as follows. The structure and framework of the proposed model are stated in Section 5.2. Mathematical formulation of the proposed DR market is presented in Section 5.3. The case study is introduced in Section 5.4, and numerical results beside discussion are brought in this Section. Some conclusions are given in Section 5.5.

5.2 Problem Statement

In this section, the framework of the proposed model is presented. The operation strategy applied for a distribution network is outlined. The market for power trading and supporting loads, as well as the market for DR trading, are elaborated. Moreover, the proposed stochastic bi-level model to operate the network and optimize the traded power and DR is briefly introduced in this section.

5.2.1 Operation Strategy

This model is in a distribution network framework which consists of different distributed energy resources (DERs), such as gas-fired thermal DG units, PVs, and WFs, along with different types of loads including critical and flexible loads. The network can be in the scale of a large distribution network operated by a DSO or a smaller scale operated by a microgrid operator.

DRAs in different nodes are in charge of DR trading with customers in the same node or eligible end-users in the other nodes. In this framework, the network operator can participate in the wholesale market represented by the ISO for power trading and buying regulation. As Figure 5.1 shows, a distribution operator or microgrid operator runs the retail market to support the related loads in the presence of different players including DRAs. Indeed, the operator runs a day-ahead market while clearing imbalances in a real-time market.

The network operator buys/sells energy from/to upstream wholesale market operated by the ISO. Regulation is also another commodity that is bought from the upstream wholesale market to cover imbalances caused by weather-dependent renewable generations. Within this framework, all the network constraints, including voltage limitation and line capacity are taken into account in the AC power flow for radial networks.

The intermittent nature of WFs and PVs are considered in the second stage to schedule the required regulation by scenario generation. In the proposed market, DRAs can bid for buying DR from customers, and the operator checks the preference of customers to sell customers' DR potential with the proposed DR bids at the same time.

To this end, in a bi-level model, customers, as active participants in the market, decide how much DR they prefer to sell to DRAs in the lower level and based on lower-level decisions, final decisions to deploy DR quantity for DRAs in the upper level are made from network operator's perspective.

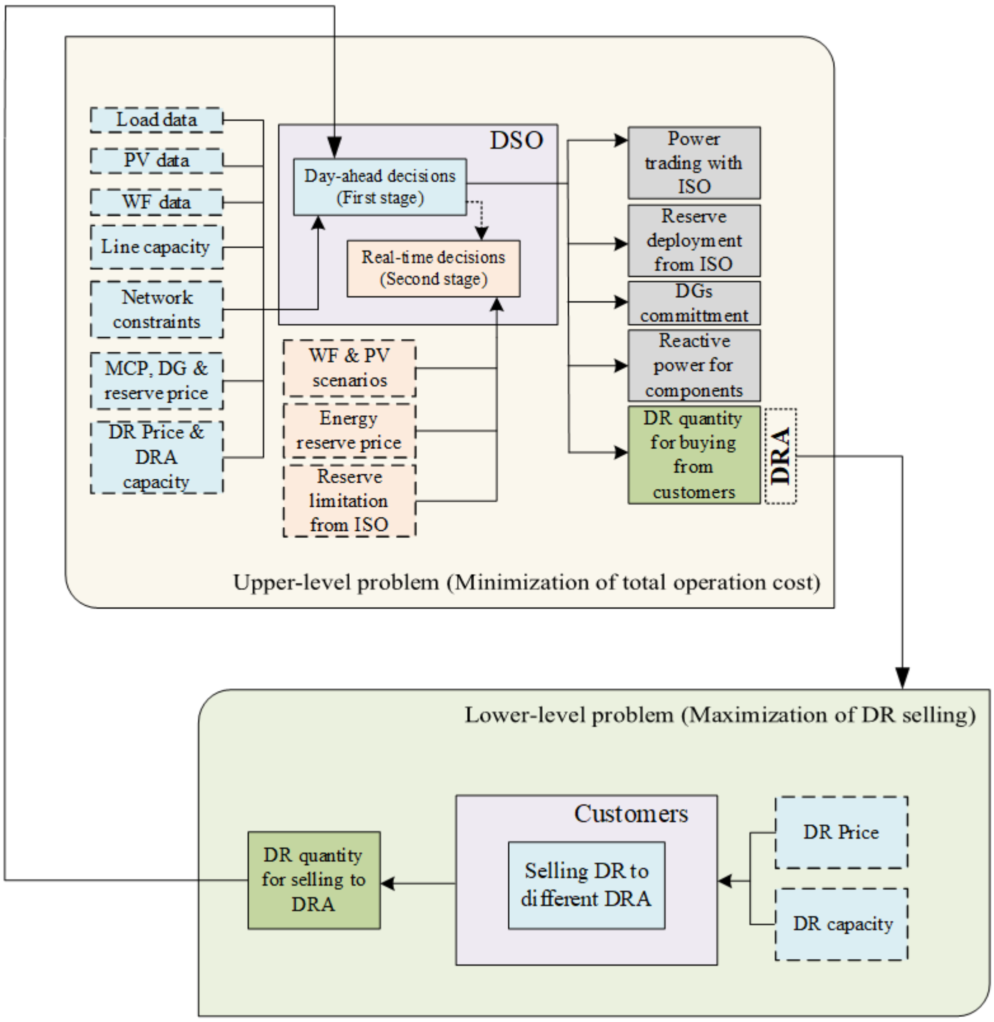


Figure 5.1 The framework of the proposed bi-level model.

5.2.2 Stochastic Bi-level Model

In the proposed bi-level model, the objective of upper-level problem is to minimize the total operation cost in the two-stage stochastic program from operator's viewpoint (DSO or microgrid operator). The first stage is for day-ahead market decisions and the second stage is for balancing decisions in the real-time market. In the first stage, power trading with the wholesale market, scheduled regulation from ISO, DGs economic dispatch, and DR quantity to be bought from customers are obtained according to market clearing price (MCP), regulation price, DGs' bidding, DR bidding by DRAs, respectively.

In the second stage, scenarios of wind and solar power outputs are generated from Monte-Carlo simulation method [199]. Real-time regulation in each scenario is defined based on real-time regulation price. Using historical data and given series of solar irradiance and wind speed, appropriate probability distribution functions (PDFs) for each variable are achieved. Based on the literature, Beta function and Rayleigh function are suitable for solar irradiance and wind speed, respectively.

The parameters of these PDFs are extracted from [101]. Generating unit random variables and dedicating to each PDF lead to obtain hourly scenarios for wind speed and solar irradiance. Thoroughly, ten thousand scenarios with the same probability are generated. To overcome the computation burden, the scenarios are reduced to ten scenarios with forward reduction method.

Afterwards, power generation of PVs and WFs are calculated from wind speed and solar irradiance scenarios according to [101]. Thus, these scenarios are applied in the second stage of the problem to achieve the required regulation. All this procedure is depicted in Figure 5.2.

Moreover, all necessary network constraints for the operation of a network at a distribution system with radial topology are considered in the first-stage of the upper level, including voltage magnitude of nodes, reactive and active power flow limitations, and current magnitude for branches are considered.

To this end, a linearized branch flow model for radial networks is employed to extract the decision variables as real, precise, and applicable as possible. In the lower level, the objective function aims to maximize the selling of DR to DRA from customers' viewpoint, and the optimal DR volume to be sold is obtained.

As mentioned, the DR volume to be bought by DRA is achieved in the upper level. Thus, the link between upper-level and lower-level problems consists of the DR quantities traded among DRA and customers.

5.2.3 DR Trading

DRAs play a key role for DR trading in this framework. They have a direct connection with customers who are eligible for DR participation. Indeed, as Figure 5.3 demonstrates, there is a bi-direction communication among DRA and customers for DR trading.

DRAs play their roles under a retail market scheme operated by DSO or microgrid operators. They bid the DR prices to buy DR from customers. Based on the DR bidding, eligible customers proceed and decide how many quantities of their DR potential they prefer to sell in order to maximize their DR selling followed by dropping their billing costs. From the DRAs' side, this trading aims to reduce the operation cost.

In the proposed DR trading method, DRAs are able to buy DR from all eligible customers in the network. It enables customers to choose the suitable DRA to sell the DR potential. As a result, competition arises among DRAs, who quote different DR prices to cater customs.

During this interaction, eligible customers freely change their DRAs. Indeed, some of the customers can sell their flexible loads as DR to the DRA at the same node or to DRAs at different nodes in each hour.

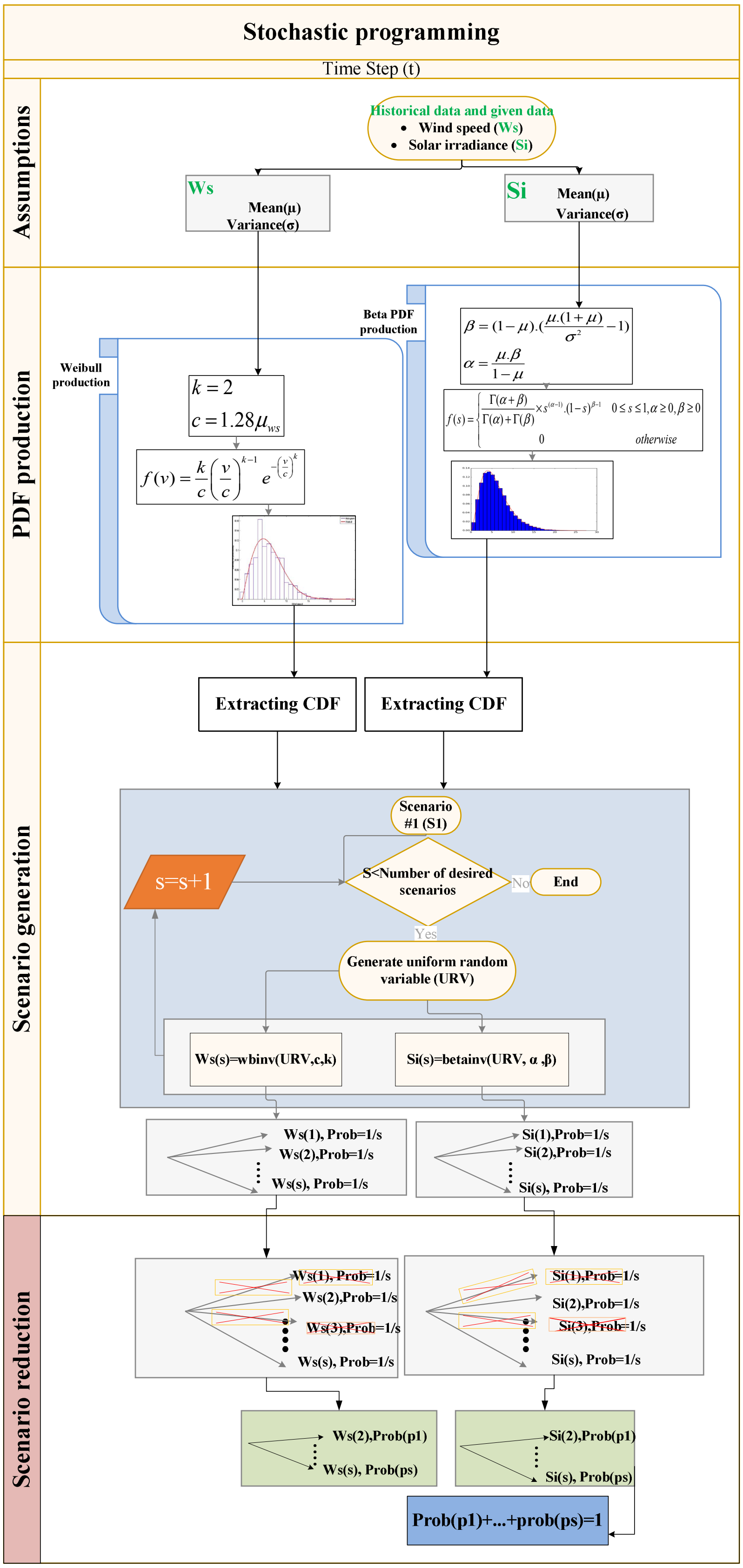


Figure 5.2 Stochastic model

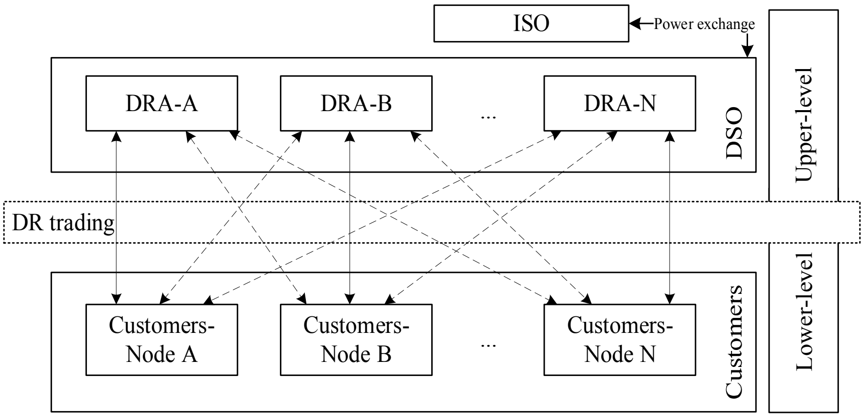


Figure 5.3. The structure of interaction among different players in the proposed model.

5.3 Problem Formulation

In this section, the stochastic bi-level programming model is formulated along with all constraints. First, the upper- and lower-level problems are presented. Then, the duality theory is implemented within the lower level. Finally, the equivalent single-level problem is set forth.

5.3.1 Bi-level Model

The upper-level objective function and relative constraints are formulated in equations (5.1) – (5.30). Accordingly, equation (5.1) is the objective function from the operator's viewpoint, which aims to minimize the total operation cost. The first two lines are related to the first stage of the two-stage problem in the day-ahead market. The decision variables are P_{tn}^{PCC}, P_{tn}^{DG}, reg_{tn}^{PCC}, P_DR_{tn}, and $P\_DR_{tnn'}^{m}$. The first term of the first line includes the cost of buying/selling power from/to upstream wholesale market with MCP. When P_{tn}^{PCC} is negative, DSO exports power to upstream network and vice versa.

The second term is the cost of buying power from the local gas-fired DG units. The third term is the regulation cost provided by the upstream network. The second line is total DR cost for all DRAs. The first term in the second line is the DR cost for DRA at node n regarding the buying DR from the customers in the same node and the second term is associated with buying DR from eligible customers to participate in DR in other nodes.

The third line is the second stage of the problem that corresponds to the security cost for buying regulation in real-time market. The decision variable here is $regs_{tns}^{PCC}$ that is the scheduled regulation from upper network for real-time market.

Equations (5.2) – (5.3) indicate active and reactive power balance for the distribution network. The second line of equation (5.2) is related to the DR quantity at each node and time period. The first term (P_DR_{tn}) is DR quantity that DRA in node n buys from customers at this node in period t and the second term ($P\_DR_{tnn'}^{m}$) is DR quantity that DRAs in other nodes buy from customers at node n. Voltage drop along distribution line is presented in (5.4).

$$
\begin{aligned}
&Minimize \sum_{t\in NT}\left\{\sum_{n\in NN}(MCP_t \times P_{tn}^{PCC} + C_{tn}^{DG}\times P_{tn}^{DG} + C_t^{reg}\times reg_{tn}^{PCC})\right.\\
&+\sum_{n\in N\_DR}(P\_DR_{tn}\times\lambda_{tn} + \sum_{\substack{n'\in N\_DR\\ n'\neq n}} P\_DR_{tnn'}^{m}\times\lambda_{tn})\\
&\left.+\sum_{s\in S} prob_s \times\left[Cs_{ts}^{reg}\times regs_{tns}^{PCC}\right]\right\}
\end{aligned}
\tag{5.1}
$$

Subject to:

<u>First stage constraints:</u>

$$
\begin{aligned}
&P_t^{PCC} + P_{tn}^{PV} + P_{tn}^{WF} + p_{tn}^{DG}\\
&+P\_DR_{tn} + \sum_{\substack{n'\in N\_DR\\ n'\neq n}} P\_DR_{tn'n}^{m}\\
&+\sum_{n'\in NN}(P_{tn'n}^{+} - P_{tn'n}^{-}) - \sum_{n'\in NN}[(P_{tnn'}^{+} - P_{tnn'}^{-}) + R_{nn'}\times I2_{tnn'}]\\
&= LD_{tn}^{Act}
\end{aligned}
\tag{5.2}
$$

$$
\begin{aligned}
&Q_t^{PCC} + Q_{tn}^{PV} + Q_{tn}^{WF} + Q_{tn}^{DG}\\
&+\sum_{n'\in NN}(Q_{tn'n}^{+} - Q_{tn'n}^{-}) - \sum_{n'\in NN}[(Q_{tnn'}^{+} - Q_{tnn'}^{-}) + X_{nn'}\times I2_{tnn'}]\\
&= LD_{tn}^{Rct}
\end{aligned}
\tag{5.3}
$$

$$
\begin{aligned}
&V2_{tn} - 2\times R_{nn'}\times(P_{tnn'}^{+} - P_{tnn'}^{-}) - 2\times X_{nn'}\times(Q_{tnn'}^{+} - Q_{tnn'}^{-})\\
&-(R_{nn'}^2 + X_{nn'}^2)\times I2_{tnn'} - V2_{tn'} = 0
\end{aligned}
\tag{5.4}
$$

$$P_{tnn'}^{+} + P_{tnn'}^{-} \le V^{Nom}\times I_{nn'}^{Max} \quad . \tag{5.5}$$

$$Q_{tnn'}^{+} + Q_{tnn'}^{-} \le V^{Nom}\times I_{nn'}^{Max} \quad . \tag{5.6}$$

$$V2_{tn}^{Nom}\times I2_{tnn'} = \sum_{\tau}(2\tau-1)\times\Delta S_{tnn'}\times\Delta P_{tnn'} + \sum_{\tau}(2\tau-1)\times\Delta S_{tnn'}\times\Delta Q_{tnn'} \tag{5.7}$$

$$P_{tnn'}^{+} + P_{tnn'}^{-} = \sum_{\tau}\Delta P_{tnn'}(\tau) \tag{5.8}$$

$$Q_{tnn'}^{+} + Q_{tnn'}^{-} = \sum_{\tau}\Delta Q_{tnn'}(\tau) \tag{5.9}$$

$$\Delta P_{tnn'}(\tau) \le \Delta S_{tnn'}, \Delta Q_{tnn'}(\tau) \le \Delta S_{tnn'} \tag{5.10}$$

$$I2_{tnn'} \le (I_{nn'}^{Max})^2 \tag{5.11}$$

$$V_{Min}^2 \le V2 \le V_{Max}^2 \tag{5.12}$$

$$V2_{tn}^{Nom} = (V^{Nom})^2 \tag{5.13}$$

$$\Delta S_{tnn'} = \frac{V^{Nom}\times I_{nn'}^{Max}}{\tau} \tag{5.14}$$

$$P_{tn}^{\bar{U}}\times tg(\cos^{-1}(-\theta)) \le Q_{tn}^{\bar{U}} \le P_{tn}^{\bar{U}}\times tg(\cos^{-1}(\theta)) \tag{5.15}$$

$$0 \le P_{tn}^{\bar{U}} \le P_{tn}^{\bar{U},Max} \tag{5.16}$$

$$P\_DR_{tn} \le \xi \times LD_{tn}^{Act} \tag{5.17}$$

$$P\_DR_{tnn'}^{m} \le \xi' \times LD_{tn}^{Act} \tag{5.18}$$

<u>Second stage constraints:</u>

$$\begin{aligned} & regs_{tns}^{PCC} + \sum_{n\in PV} (Ps_{tns}^{PV} - P_{tn}^{PV}) + \sum_{n\in WF} (Ps_{tns}^{WF} - P_{tn}^{WF}) \\ & + \sum_{n'\in NN} (Ps_{tn'ns}^{+} - Ps_{tn'ns}^{-}) - (P_{tn'n}^{+} - P_{tn'n}^{-}) \\ & - \sum_{n'\in NN} [(Ps_{tnn's}^{+} - Ps_{tnn's}^{-}) + R_{nn'} \times I2s_{tnn's}] - [(P_{tnn'}^{+} - P_{tnn'}^{-}) + R_{nn'} \times I2_{tnn'}] = 0 \end{aligned} \tag{5.19}$$

$$\begin{aligned} & Qs_{tns}^{PCC} + \sum_{n\in PV} (Qs_{tns}^{PV} - Q_{tn}^{PV}) + \sum_{n\in WF} (Qs_{tns}^{WF} - Q_{tn}^{WF}) \\ & + \sum_{n'\in NN} (Qs_{tn'ns}^{+} - Qs_{tn'ns}^{-}) - (Q_{tn'n}^{+} - Q_{tn'n}^{-}) \\ & - \sum_{n'\in NN} [(Qs_{tnn's}^{+} - Qs_{tnn's}^{-}) + X_{nn'} \times I2s_{tnn's}] - [(Q_{tnn'}^{+} - Q_{tnn'}^{-}) + X_{nn'} \times I2_{tnn'}] = 0 \end{aligned} \tag{5.20}$$

$$\begin{aligned} & V2s_{tns} - 2\times R_{nn'} \times (Ps_{tnn's}^{+} - Ps_{tnn's}^{-}) - 2\times X_{nn'} \times (Qs_{tnn's}^{+} - Qs_{tnn's}^{-}) \\ & -(R_{nn'}^{2} + X_{nn'}^{2}) \times I2s_{tnn's} - V2s_{tn's} = 0 \end{aligned} \tag{5.21}$$

$$V2_{tn}^{Nom} \times I2s_{tnn's} = \sum_{\tau} (2\tau - 1) \times \Delta S_{tnn'} \times \Delta Ps_{tnn's} + \sum_{\tau} (2\tau - 1) \times \Delta S_{tnn'} \times \Delta Qs_{tnn's} \tag{5.22}$$

$$Ps_{tnn's}^{+} + Ps_{tnn's}^{-} = \sum_{\tau} \Delta Ps_{tnn's}(\tau) \tag{5.23}$$

$$Qs_{tnn's}^{+} + Qs_{tnn's}^{-} = \sum_{\tau} \Delta Qs_{tnn's}(\tau) \tag{5.24}$$

$$\Delta Ps_{tnn's}(\tau) \le \Delta S_{tnn'}, \Delta Qs_{tnn's}(\tau) \le \Delta S_{tnn'} \tag{5.25}$$

$$I2s_{tnn's} \le (I_{nn'}^{Max})^{2} \tag{5.26}$$

$$Ps_{tns}^{\bar{U}} \times tg(\cos^{-1}(-\theta)) \le Qs_{tns}^{\bar{U}} \le Ps_{tns}^{\bar{U}} \times tg(\cos^{-1}(\theta)) \tag{5.27}$$

$$Ps_{tnn's}^{+} + Ps_{tnn's}^{-} \le V^{Nom} \times I_{nn'}^{Max} \tag{5.28}$$

$$Qs_{tnn's}^{+} + Qs_{tnn's}^{-} \le V^{Nom} \times I_{nn'}^{Max} \tag{5.29}$$

$$V_{Min}^{2} \le V2s \le V_{Max}^{2} \tag{5.30}$$

Lower-level:

$$Max \sum_{t\in NT} \sum_{n\in N\_DR} (P\_DR_{tn} \times \lambda_{tn} + \sum_{\substack{n'\in N\_DR \\ n'\neq n}} P\_DR_{tnn'}^{m} \times \lambda_{tn'}) \tag{5.31}$$

$$\sum_{n\in N\_DR} (P\_DR_{tn} + \sum_{\substack{n'\in N\_DR \\ n'\neq n}} P\_DR_{tnn'}^{m}) \le \sum_{n\in N\_DR} Total\_DR_{tn} : \Omega_{tn} \tag{5.32}$$

$$P\_DR_{tn} \le IDR_{tn}^{MAX} : \Gamma_{tn} \tag{5.33}$$

$$P\_DR_{tnn'}^{m} \le MDR_{tn'}^{MAX} : \Psi_{tnn'} \tag{5.34}$$

Active and reactive power limitations are presented in equations (5.5) – (5.6), respectively. Active and reactive power flows in the distribution network are presented in equations (5.7) – (5.14), where linearization of active and reactive power is conducted by equation (5.7), and piecewise linearization of constraints is performed by equations (5.8) – (5.14), [190]. Power factor constraint is brought in inequality in equation (5.15).

The limitation of power exchange and power production for different elements in the network is represented in equation (5.16); the maximum possible demand response quantity to be bought by each DRA from eligible customers in the same node and other nodes are presented in equations (5.17) – (5.18), respectively. Equations (5.19) – (5.30) indicate the second-stage constraints of the two-stage problem in the upper level.

Balancing constraints for active and reactive power for different scenarios in the real-time market are calculated by equations (5.19) and (5.20), respectively. Voltage drop equation for scenarios in the second stage is in equation (5.21), and constraints linearization regarding branch power flow for dealing with scenarios in the real-time market are represented in equations (5.22) – (5.26). Power factor constraint, active and reactive power limitations, and voltage limitation to meet network requirement for scenarios are in equations (5.27) – (5.30), respectively.

The lower-level objective function which aims to maximize the income from DR selling by customers is presented in equation (5.31). It includes two terms, the first one represents the income from selling DR to DRA in the same node, and the second one is the income from selling DR to DRA in other nodes.

The constraints of this problem are in equations (5.32) – (5.34). Inequality in equation (5.32) indicates that the total sold DR quantity should be lower than the total percentage of the loads. This inequality is the same for DRA and buying DR. the limitation of DR selling for customers in different nodes are given in (5.33) – (5.34) where (5.33) is the capacity of DR selling to DRA in the same node and (5.34)is the capacity of DR selling to DRAs in other nodes.

5.3.2 Dual Form of the Lower-Level Problem

Given DR prices, the lower-level problem from equations (5.31) – (5.34) renders a linear program, and strong duality always holds true [155]. Its dual form reads as follows:

$$Min \sum_{t \in NT} \sum_{n \in N\_DR} (Total\_DR_{tn} \times \Omega_{tn} + IDR_{tn}^{MAX} \times \Gamma_{tn} + \sum_{\substack{n' \in N\_DR \\ n' \neq n}} MDR_{tn'}^{MAX} \times \Psi_{tnn'}) \tag{5.35}$$

$$\Omega_{tn} + \Gamma_{tn} \geq \lambda_{tn} \tag{5.36}$$

$$\Omega_{tn} + \sum_{\substack{n' \in N\_DR \\ n' \neq n}} \Psi_{tnn'} \geq \sum_{\substack{n' \in N\_DR \\ n' \neq n}} \lambda_{tn'} \tag{5.37}$$

$$\Omega_{tn}, \Gamma_{tn}, \Psi_{tnn'} \geq 0 \tag{5.38}$$

where Ω_{tn}, Γ_{tn} and $\Psi_{tnn'}$, $\Psi_{tnn'}$ are dual variables defined in equations (5.32) – (5.34) following the colon. Dual form from equations (5.35) – (5.38) will help build the single-level equivalence of the bi-level problem.

5.3.3 Equivalent Single-Level Problem

To systematically solve the bi-level problem, it should be turned into a one-level problem which can be recognized by off-the-shelf solvers. According to strong duality theorem, if a primal feasible point satisfying equations (5.32) - (5.34), and a dual feasible point satisfying equations (36)-(38), lead to the same value for the primal objective from equation (5.31) and dual objective from equation (5.35), then, the pair of primal and dual points solves the respective problem [155].

To this end, the lower-level problem can be replaced by its primal-dual optimality condition, which appears in the form of constraints without an objective function to be optimized. It consist of equations (5.32) - (5.34), equations (5.36) - (5.38), and equality equation (5.39).

$$\sum_{t\in NT}\sum_{n\in N\_DR}(Total\_DR_{tn}\times\Omega_{tn}+IDR_{tn}^{MAX}\times\Gamma_{tn}+\sum_{\substack{n'\in N\_DR\\ n'\neq n}}MDR_{tn}^{MAX}\times\Psi_{tnn'})= \\ \sum_{t\in NT}\sum_{n\in N\_DR}(P\_DR_{tn}\times\lambda_{tn}+\sum_{\substack{n'\in N\_DR\\ n'\neq n}}P\_DR_{tnn'}^{m}\times\lambda_{tn'}) \tag{5.39}$$

Finally, the one-level equivalence of the proposed bi-level problem containing all upper- and lower-level constraints can be formulated as:

$$Minimize\ (5.1) \tag{5.40}$$

Subject to:

$$equations\ (5.2) - (5.30), \tag{5.41}$$

$$equations\ (5.32) - (5.34),\text{ and} \tag{5.42}$$

$$equations\ (5.36) - (5.39) \tag{5.43}$$

The problem, from equations (5.40) - (5.43), is a linear program and can be easily solved by existing solvers.

5.4 Case Study and Numerical Results

In this section, the proposed method is evaluated in a 15-bus distribution network. First, the case study is introduced, and then the result of implementing the proposed approach on the test system is brought and discussed.

5.4.1 Case Study

A 15-bus IEEE distribution system with nominal power 2300 kW is applied which is in Figure 5.4 [202]. It includes four thermal DG units (690kW each), two PV systems (100kW each) and two WTs (100kW each). Market clearing price (MCP), regulation price, and DG production price are shown in Figure 5.4. These prices along with PV systems and WT farms information are extracted from Spanish market [203].

The proposed model can be easily extended to any realistic-sized network. While we believe the main findings of current work are regardless of a test system. In this work, two cases are considered to analyze different states of the proposed model. In the first case, only two DRAs are taken into account. In this case, the interaction of these two DRAs to run DR trading especially in terms of their competition is studied.

In the second case, the impact of adding more DRAs in the network on the total operation cost, DR cost, buying power from DGs and the wholesale market as well as selling power to wholesale market are investigated. The potential of DR participation would be twenty percent, moreover, ξ, ξ' are 10 and 4.5%, respectively. The problem is solved by calling CPLEX solver in GAMS [204]. The simulation platform is a laptop with 2.7GHz core i7 processor and 8GB RAM. The solver time is 1.52 seconds.

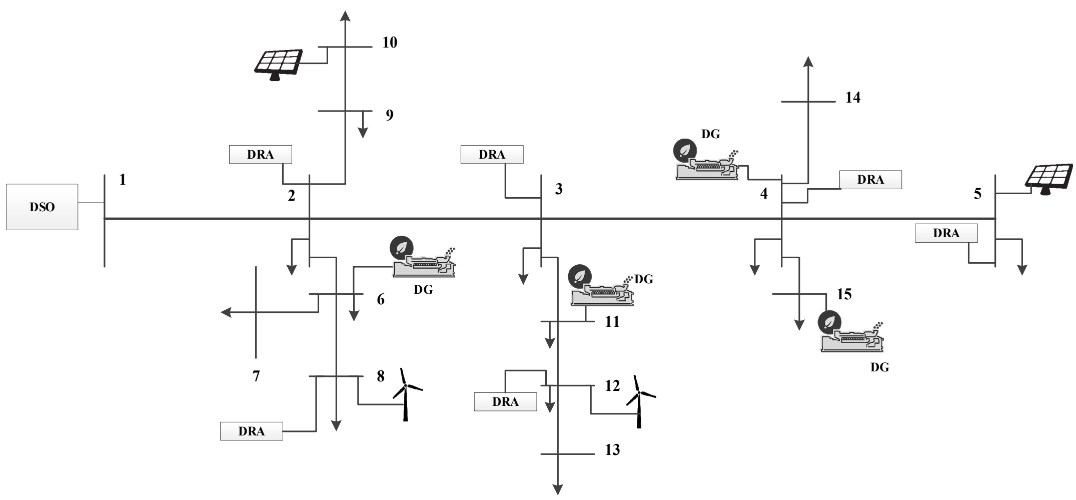


Figure 5.4. 15-bus distribution network.

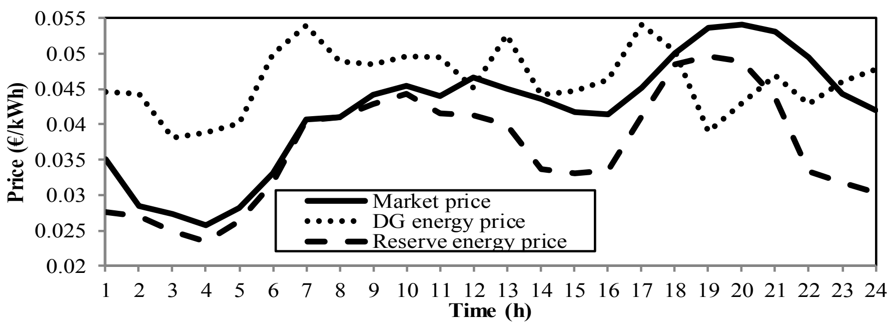


Figure 5.5 Hourly different prices.

5.4.2 Numerical Results

5.4.2.1 Case 1: Two DRAs in Two Nodes

In case 1, two DRAs at node 3 and node 5 are considered. Each one can buy DR from the customers in their node and the customers from the other DRA. With the definition of 7 scenarios which contain different DR prices for these two DRAs, the interaction among DRAs and customers to exchange the DR is compared. In other words, according to the DR prices, the quantity of DR is scheduled in a competitive way.

It is noteworthy that scenario 1 to scenario 5 consider fixed DR prices for the whole day (Table 5.1), while time-varying DR prices are considered for scenario 6 and scenario 7 (Figure 5.6). Scenario 7 is the reverse of scenario 6. It means the price for DRA3 in scenario 6 is replaced by DRA5 and vice versa.

The results of the implementation of these scenarios with the proposed bi-level model are demonstrated in different figures and compared. Based on these figures, the hourly scheduled DR quantities during a day are compared with each other along with eligible DR capacity for each node. Noted that DRA3-5 is the purchased DR by DRA3 from customers in node 5 from DSO's viewpoint. This definition is vice versa for DRA5-3.

As can be seen, the DR capacity in node 3 is larger than those in node 5 during a day, because node 3 has more load consumption than node 5. Once the DR price for DRA5 is higher, a lower DR quantity is scheduled for DRA5 and DRA5-3 based on Figure 5.7 and Figure 5.11. This occurs despite the fact that from the customers' viewpoint, they prefer to sell more DR to DRAs because the objective function from the customers' viewpoint is to maximize selling DR quantity.

Moreover, the customers' effort is more successful when the DR price is much higher particularly in scenario 1 and more DR quantity is scheduled for DRA5. The opposite phenomena happen when DR price for DRA3 is higher according to the Figure 5.8 and Figure 5.10. The difference is that no DR is scheduled for DRA3 and DRA3-5 in the first hours of the day as off-peak hours which means all customers' attempt to sell the DR with higher price does not work well at those hours in DRA3.

Therefore, high DR price does not lead to higher scheduled DR for DRA3 because node 3 has a DG compared with node 5 and it is possible to support loads in node 3 more economically than applying DR. Moreover, the more reasonable the DR prices would be, the more DR quantities are scheduled. Noted that the reasonable price is one closer to the market price (Figure 5.5) which is obvious in Figure 5.9, Figure 5.10, Figure 5.12, and Figure 5.13.

In scenario 3, that presents the state of the same DR price for two DRAs, the popularity of DRA selection can be compared. The DR prices are lower than MCP in peak hours; hence, it is cost-efficient to have load reduction as much as possible for both stakeholders.

At off-peak hours, just DRA5 and DRA5-3 are scheduled to have load reduction. Most probably the reason behind this fact is due to the existence of two DERs, one WF and one thermal DG unit, which supply all loads with low cost in node 3 and there is no need for DR.

Table 5.1 Different DR prices for DRA3 and DRA5 (5 scenarios)

DR price (€/kWh)	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
DRA-3	0.09	0.09	0.04	0.04	0.04
DRA-5	0.3	0.4	0.04	0.035	0.09

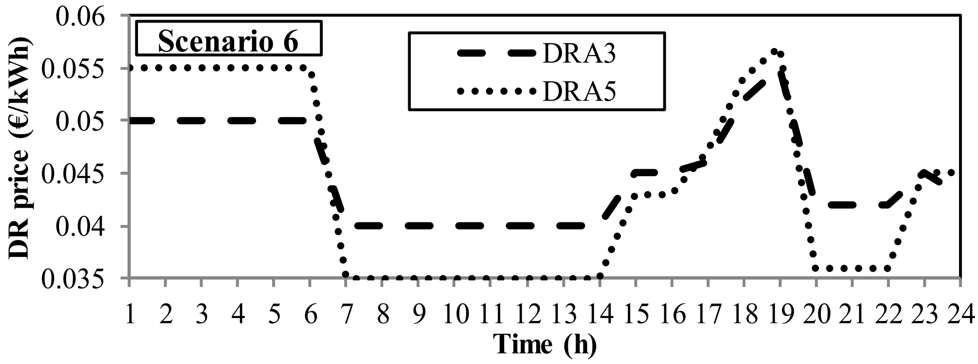


Figure 5.6 DR prices for DRA3 and DRA5 in different hours. (scenario 6)

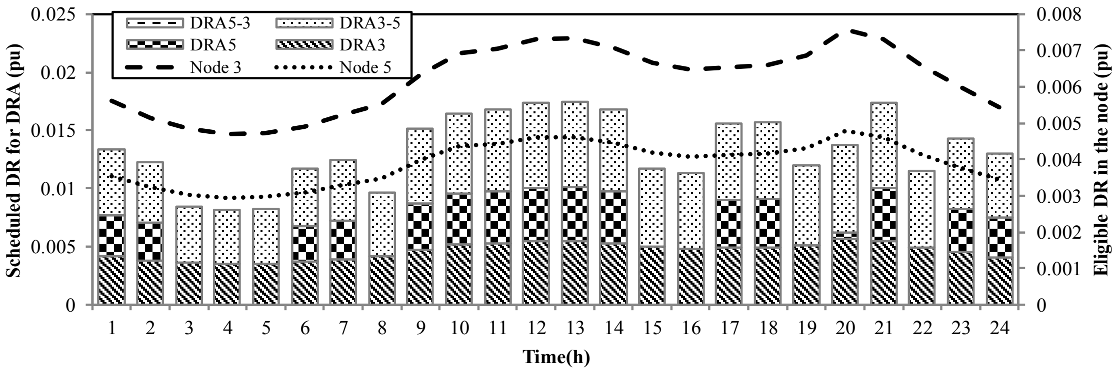


Figure 5.7 Scenario 1 results.

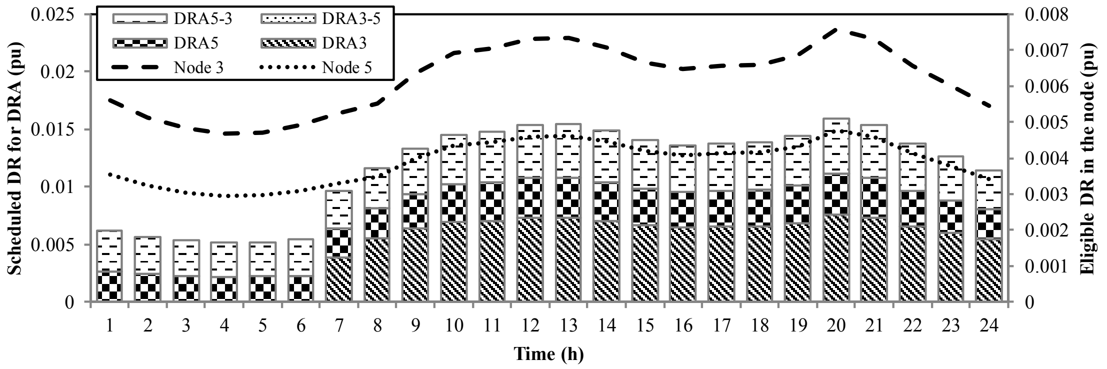


Figure 5.8 Scenario2 results.

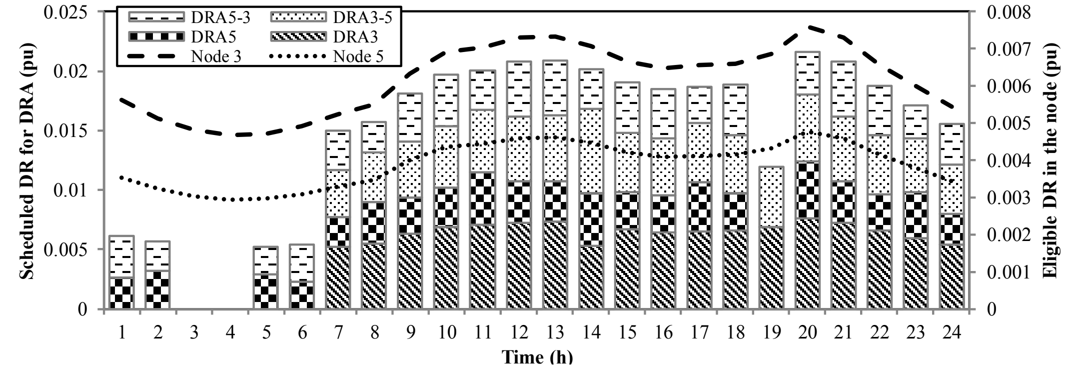


Figure 5.9 Scenario 3 results.

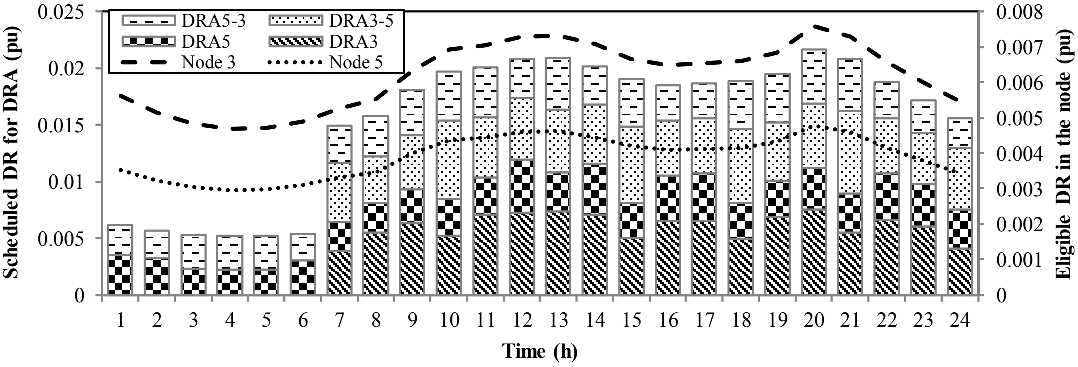


Figure 5.10. Scenario 4 results.

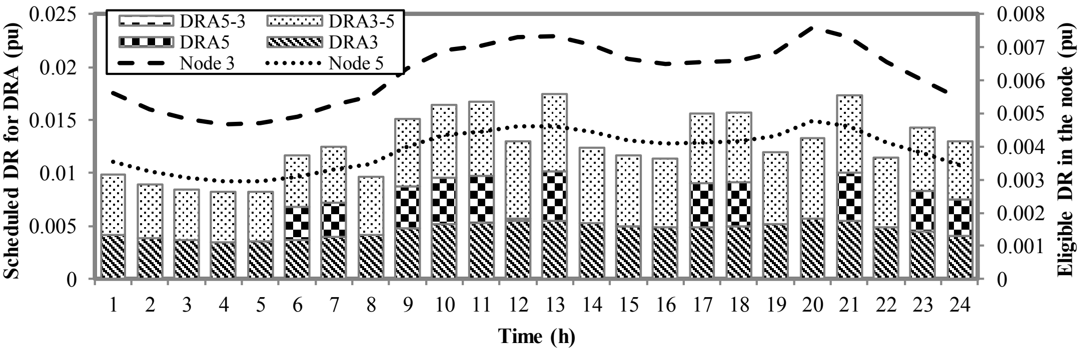


Figure 5.11. Scenario 5 results.

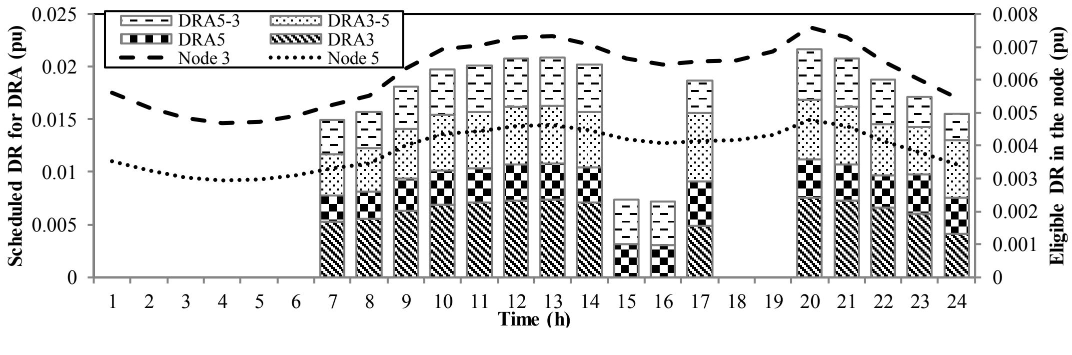


Figure 5.12 Scenario 6 results.

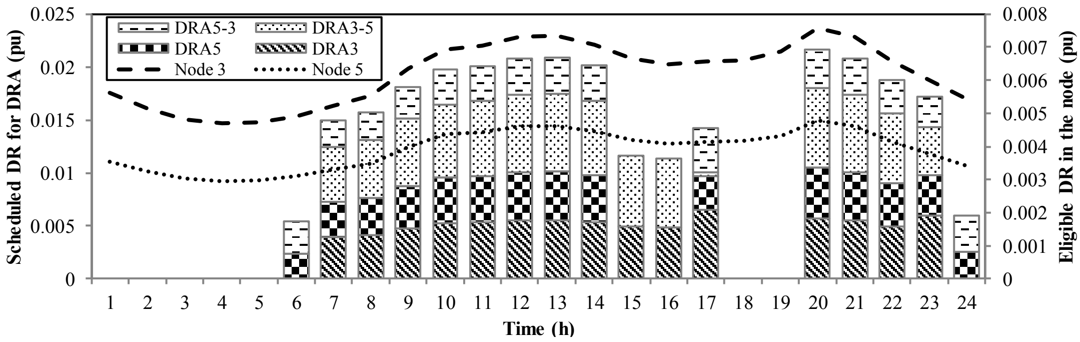


Figure 5.13 Scenario 7 results.

The results shown in Figure 5.12 and Figure 5.13 demonstrate that once the DR prices are defined based on peak hours and MCP, the results are more desirable. Thoroughly, at off-peak hours and the hours with lower MCP including 1-6 and 18-19, almost no DR is scheduled because of the DR prices higher than the MCP.

Moreover, at peak-hours, approximately, maximum possible DR quantities are exchanged among DRA and customers, no matter which DRA has the higher or lower DR price. At hours 15 and 16, although the MCP is lower than DR prices, DR is scheduled because the production cost of DGs is higher than the MCP and no DG is scheduled to generate power at those hours. Thus, to overcome this power shortage, DR is the lowest-cost solution.

For scenario 6, DRA5 and DRA5-3 are just scheduled in periods 15 and 16 due to the lower price, and for scenario 7 is vice versa. DG production price in period 17 is much higher and not only no DG is committed, but also more DR quantities are scheduled, since the MCP and DR prices have no much difference.

5.4.2.2 Case2: Several DRAs

In the second case, multiple DRAs are taken into account, and the impact of adding DRAs on each DRA's cost and total DR cost are investigated. The impact of the number of DRAs on the cost of DR for each DRA is demonstrated in Figure 5.14. As can be seen, after adding DRA in node 2, DR cost for DRA3 becomes lower and for DRA5 becomes higher because of the need to apply DR for node 3 when adding DRA2 declines, and on the other side the DR interaction between node 2 and node 5 as DRA5-2 leads to an increase in DR cost for DRA5.

Total DR cost for hours 2 to 5 between 2 and 3 DRAs has no difference according to Figure 5.15, because DR scheduling does not change at those hours with two DRAs and three DRAs. Moreover, since DRA3 has more DR capacity, a higher DR quantity is scheduled, and the total DR price is higher for DRA3 compared with DRA5 and DRA2.

After adding DRA in node 4, DRA4 will have the highest DR cost because of having highest DR capacity followed by the higher level of DR scheduling. Moreover, the hourly total DR cost has a growing tendency after adding DRA4 based on Figure 5.15.

This trend continues after adding DRA8 and DRA12, because, as it is clear in Figure 5.15, the cost of DR increases because with the existence of more DRAs, the operator prefers to have more DR quantity which is more cost-efficient to provide the demand-supply balance. In other words, scheduled DR is sometimes cheaper for operators and several DRAs make it much cheaper, although the DR cost may increase.

Likewise, the DR cost for each DRA after adding another DRA has an increasing trend, since as mentioned; each DRA will have an interaction with the loads in the new node for DR exchange, which causes extra cost for existing DRAs.

Figure 5.16 demonstrates the hourly power generation of DG units and hourly exchange power with the upper network in the presence of six DRAs. As it is obvious, when the MCP is higher, the operator prefers to supply the loads by inside DGs and sell the extra power to ISO.

Therefore, at hours 12 and 19-22, all DGs are committed almost at their maximum capacity to not only supply the consumption but also to make a profit from selling the extra power to the market. At other hours, depending on the MCP and DG production prices, the required power is bought from the market or from DGs. For example, at hours 8-11 and 15-17, since the DG production price is higher than the MCP, the operator buys electric power from ISO instead of using DGs.

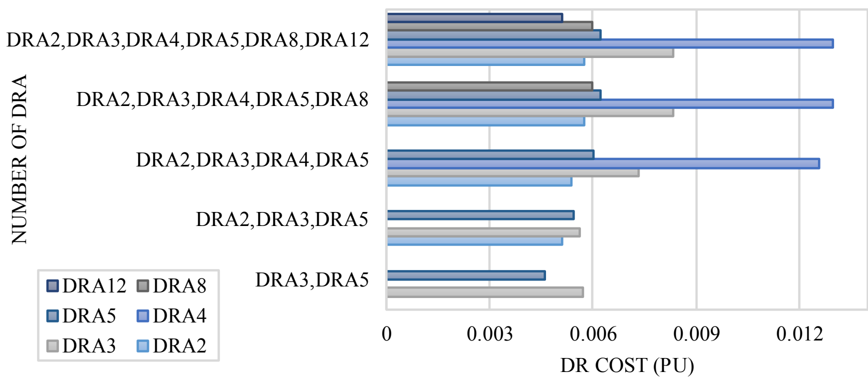


Figure 5.14. DR cost for each DRA in different numbers of DRAs in the network.

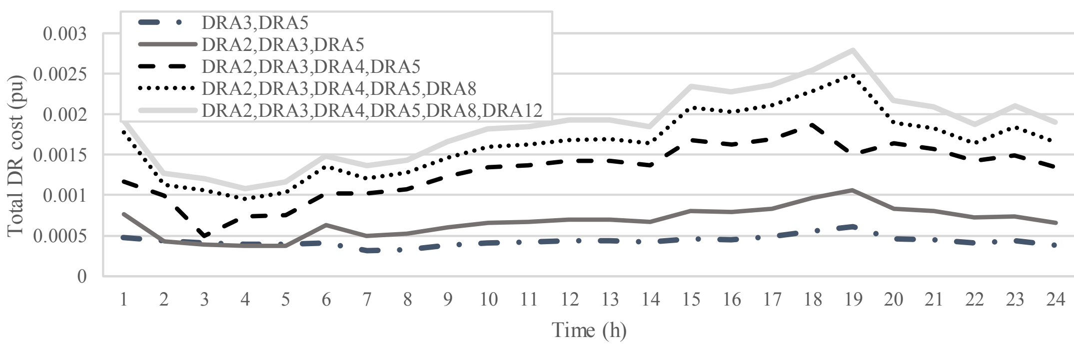


Figure 5.15. Hourly total DR cost for different numbers of DRA in the network.

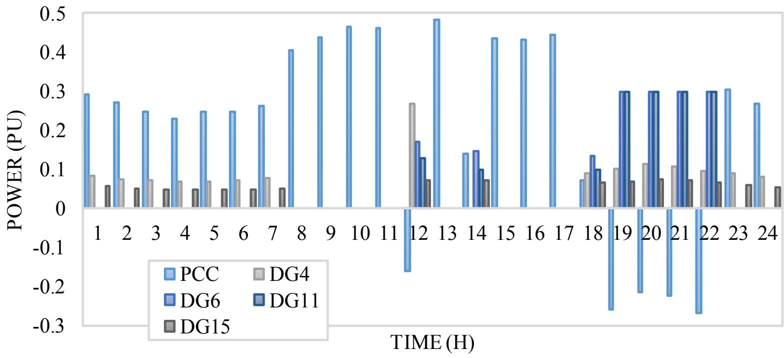


Figure 5.16. Hourly power generation of DGs and power exchange with the upper network.

5.5 Brief Remarks of the Chapter

The proposed innovative method is able to optimize the DR quantity to be bought/sold by DRA/customers from/to customers/DRAs, simultaneously, within the distribution network. To this end, all the relative elements of a real distribution network such as capacity line, voltage limitation, as well as RESs uncertainties were modeled in a bi-level program and in a retail market framework.

The upper-level problem was from operator's viewpoint, with considering DRAs, enabled to buy DR, seeking to minimize total operation cost. The lower-level problem was from customers' viewpoint and tends to maximize the potential of selling DR to DRAs. According to the results, there was a competition among DRAs to buy DR.

The DRA with lower DR prices, especially in the moderate DR prices, was more successful to be selected by customers. With high DR prices, customers could sell more; nevertheless, DRAs disliked buying in this case. Likewise, results showed that it would be better to define the DR prices according to the MCP and peak hours. Moreover, the impact of the existence of DG or RES in a node on scheduled DR for customers or DRAs of that node was proved.

Adding more DRAs and more eligible customers in different nodes, sometimes, could lead to a decrease in scheduled DR for pre-placed DRAs due to providing required DR by new potential participants. While, most of the time DR was more cost-efficient to be scheduled even if a new DRA was added. Moreover, the DR cost for each DRA rose after adding another DRA because of adding an interaction DR cost among new potential DR and previous DRA.

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 1.6, are summarized as follows. For the sake of clarity the research questions are reproduced here.

- ***What are the current solutions for modelling the stochastic nature of renewable energy resources and how to cope with the negative impacts of these sources of uncertainty on power system scheduling?***

With high penetration of RESs in different sections of the network, accurate scheduling of the system is going to be a big challenge for system operators. The accuracy in power systems operation is essential, since many important factors of the network such as operation cost, stability, sustainability and security have close tie to it.

When RESs with high source of uncertainties are in the network, obtaining a precise scheduling would be difficult. Therefore, lots of researchers have put the effort to overcome this problem which had been brought in **Chapter 2**. Accordingly, the offered approaches can be classified into mathematical methods, providing flexibilities like demand-side management and electricity market strategies. In terms of mathematical methods, it is possible to divide all methods in two main categories: methods for independent variables and for dependent ones.

If there are several stochastic variables in the studied case and there is no connection and correlation among them, independent approaches should be applied. These methods include: point forecasts, probabilistic forecast, and scenario forecast. On the other side, in some cases, stochastic variables have some correlations which are not possible to study and model them, separately.

In this case, dependent methods such as product moment correlations, rank correlation, and copula should be employed. Moreover, this dependency may have several dimensions and multi-dimensional methods, including graphical tree model, graphical vine model, and risk-averse model, should be taken into account.

All these mathematical models can have some errors, though. Therefore, operators try to utilize some other strategies in the network beside mathematical models which has been explained in **Chapter 2**. One of these strategies is demand-side management, which can be explained as the ability of customers to help operators to tackle unpredicted behavior of RESs in real-time.

Indeed, having been given some incentives to customers, operators encourage customers to participate in network management when it is necessary. Consumption reduction or shifting unnecessary electricity usage is handled in some methods to make the balance among demand and supply in case RESs production is less than what it's expected.

Another strategy would be defining different market schemes to diminish the negative impacts of RESs on scheduling. Different optimization strategies in day-ahead market, balancing market, intra-day market besides defining new markets like demand response exchange market are the solution for short-term scheduling of power system operators.

- ***What is the best market scheme to operate a power system with high penetration of wind power generation within the transmission network (wholesale market) and how to apply the potential of the DRA as an active market player?***

If ISO run a pre-emptive market, which considers a coordination of day-ahead market and real-time market, not only uncertainties raised by RESs are tackled through a market scheme and mathematical model like MCS, but also DR can be implemented through the concept of DRA. Indeed, with a stochastic two-stage programming approach the pre-emptive market is modeled from ISO's viewpoint. MCS is employed to generate scenarios that reflect the behavior of RESs in real-time.

Also, the final decisions in day-ahead market such as unit commitment, reserve deployment as well as demand response would be made based on the analysis of that scenarios in the real-time market. To take the biggest advantage of DRAs for DR implementation, a bi-level model should be employed in a way that ISO would minimize the total operation cost in the upper level and DRAs would maximize their profit in the lower level of the problem.

In this case, the interaction of ISO and DRAs has been taken into account, which leads to more optimized results for decision variables, especially the DR quantities during the horizon time. One of the best DR options to use is LC, LS, and LR, although other kinds of DR programs can be applied. All these novel methodologies have been performed in **Chapter 3.**

The results of running this model on a 6-bus IEEE test system proved that not only DR quantity is much more optimized compared with when DRA's perspective was not considered in the problem, but also the operation cost is much lower.

- ***How to employ the possible extra potential of customers in the real-time market to participate in demand-side management, while their potential in day-ahead market has already been taken into account?***

The extra potential of customers for DR participation comes from unexpected events occurred in real-time because of the uncertain behavior of RESs generation or load demand. If there is an approach to model this unexpected behavior, it is possible to apply the DR potential caused by it. In **Chapter 4**, the uncertainty of WPGs is modeled by MCS and relative PDFs at each time step regarding wind generation.

Accordingly, a large number of scenarios reflecting the unexpected behavior of wind power are generated and by a suitable reduction method, these numbers are dropped to a few ones as the main samples. DR is modeled in real-time for each scenario as a two-stage stochastic programming in order to optimize the DR quantity in the real-time market in addition to the day-ahead one.

This modeled has been performed in the 6–bus IEEE test system as well as the RTS-96 to prove the capability of running this novel methodology in all kinds of networks. The results have shown a proper implementation of DR in the real-time market for different possible scenarios and a decrement in total operation cost compared to when this DR potential has not been taken into account in real-time.

- ***How to apply demand-side management in the distribution network (retail market) when DRAs are responsible for DR trade-off and customers are playing an active role to benefit from this opportunity in an uncertain environment?***

A bi-level optimization programming is applied to model the distribution network, which includes several DRAs in the upper level and consider the customers in the lower level. In this model, DR quantity traded by DRAs with customers is optimized within the framework of a retail market, described in **Chapter 5**.

As the distribution network includes RESs and their uncertainty has a strong impact on the DR scheduling, their stochastic nature is modeled by MCS to generate scenarios and to use the two-stage programming in order to make final decisions such as DGs production, selling/buying power from/to the upstream network and DR quantity.

Therefore, the market model is like running a day-ahead market while the coordination of the real-time market is taken into account by the DSO. At the same time, customers try to maximize their DR participation to decrease their billing cost. During this procedure, the DRA is responsible to trade DR with three available options, including LC, LS, and LR.

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:

- Considering uncertainty in demand-side management and availability of DR could be studied in the future;
- Customers' comfort is a factor that influences scheduling. Therefore, to extend the current model, it is suggested to add customers' comfort factor;
- Customers should be enabled to choose the DRAs. Therefore, providing a competition environment for DRAs is another suggestion for developing the proposed model;
- DR models can be developed in more detail with more constraints. Therefore, extending the DR models is proposed for studying in the future.

6.3 List of Publications

6.3.1 Book Chapters

1. **S. Talari**, M. Shafie-khah, N. Hajibandeh, J.P.S. Catalão, "Assessment of ancillary service demand response and time of use in a market-based power system through a stochastic security constrained unit commitment", 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. 233-241, May 2017.
   http://dx.doi.org/10.1007/978-3-319-56077-9_22

6.3.2 Publications in Peer-Reviewed Journals

1. **S. Talari**, M. Shafie-khah, Y. Chen, W. Wei, P.D. Gaspar, J.P.S. Catalão, "Real-time scheduling of demand response options considering the volatility of wind power generation", **IEEE Transactions on Sustainable Energy**, 2019 (forthcoming).
   https://doi.org/10.1109/TSTE.2018.2868449

2. **S. Talari**, M. Shafie-khah, F. Wang, J. Aghaei, J.P.S. Catalão, "Optimal scheduling of demand response in pre-emptive markets based on stochastic bilevel programming method", **IEEE Transactions on Industrial Electronics**, Vol. 66, No. 2, pp. 1453-1464, February 2019.
   http://dx.doi.org/10.1109/TIE.2017.2786288

3. **S. Talari**, M. Shafie-khah, G.J. Osório, J. Aghaei, J.P.S. Catalão, "Stochastic modelling of renewable energy sources from operators' point-of-view: a survey", **Renewable and Sustainable Energy Reviews** (**ELSEVIER**), Vol. 81, pp. 1956-1968, January 2018.
   http://dx.doi.org/10.1016/j.rser.2017.06.006

4. **S. Talari**, M. Shafie-khah, G.J. Osório, F. Wang, A. Heidari, J.P.S. Catalão, "Price forecasting of electricity markets in the presence of a high penetration of wind power generators", **Sustainability**, Vol. 9, No. 11, pp. 1-13, November 2017.
   http://dx.doi.org/10.3390/su9112065

5. **S. Talari**, M. Shafie-khah, P. Siano, V. Loia, A. Tommasetti, J.P.S. Catalão, "A review of smart cities based on Internet of things concept", **Energies**, Vol. 10, No. 4, pp. 1-23, April 2017.
http://dx.doi.org/10.3390/en10040421

6.3.3 Publications in International Conference Proceedings

1. **S. Talari**, M. Shafie-khah, F. Wang, J.P.S. Catalão, "Coordinated scheduling of demand response aggregators and customers in an uncertain environment", in: Proc. 20th Power Systems Computation Conference — ***PSCC 2018*** (technically co-sponsored by **IEEE**), Dublin, Ireland, USB flash drive, June 11-15, 2018.
https://doi.org/10.23919/PSCC.2018.8442721

2. **S. Talari**, M. Shafie-khah, M.R. Haghifam, M. Yazdaninejad, J.P.S. Catalão, "Short-term scheduling of microgrids in the presence of demand response", in: Proc. 7th **IEEE** PES International Conference on Innovative Smart Grid Technologies — ***ISGT Europe 2017***, Torino, Italy, USB flash drive, September 26-29, 2017.
https://doi.org/10.1109/ISGTEurope.2017.8260306

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