New Demand Response Framework and Its Applications for Electricity Markets

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ABSTRACT

Demand Response (DR) refers to modifications to electricity usage by consumers, which are derived by changes in the price of electricity or incentive payments offered to induce lower electricity use at specific periods. DR is a useful tool for not only electricity market players on both the supply and demand sides, but also Independent System Operators (ISO). On the supply side, DR is of particular interest for wind power producers, where they can use DR to alleviate their production intermittency as well as real-time market price variations. In addition, electricity retailers on the demand side may use DR to procure part of their clients’ energy and consequently cope with pool market price fluctuations. Furthermore, ISOs are faced with new challenges as the integration of renewable resources increases, and therefore may seek DR as a reserve provider.

Despite the clear understanding of DR benefits for the above market players, they have practically low involvement in DR programs. They instead prefer to buy DR products from a third-party company. Such a company is called a DR aggregator, which is responsible for carrying out DR programs on consumers and selling the outcome to purchasers. To this end, an appropriate DR framework is needed to provide mutually attractive DR deals between the aggregator and DR purchasers.

This research aims at proposing a new DR framework through which DR is traded as a public good between a DR aggregator and a DR purchaser. Various bilateral DR contracts with unique features are proposed and formulated for this purpose. The proposed DR framework is then applied to an offering strategy by wind power producers. Two well-known markets, i.e. the Australian National Electricity Market (NEM) and the Nordic market, are studied and proper wind offering plans in these markets are formulated. In addition, the behaviour of DR aggregators in power offering by a wind power producer is modelled. A bilevel problem is formulated in which the upper level refers to the wind power producer and the lower level models the DR aggregator behaviour. Furthermore, DR application by a strategic wind power producer, being able to alter market prices, is evaluated. To this end, a bilevel model is formulated in which the leader is the strategic wind power producer and followers are the market clearing mechanism and DR aggregator behaviour, respectively. The proposed DR framework is also applied to an energy procurement problem of electricity retailers. A cost minimization problem is modelled through which a retailer can purchase DR in addition to the commonly-used pool market and forward contracts. Lastly, the application of DR in an electricity market integrating high penetration of wind and PV resources is studied. A market dispatch is
formulated in which an ISO allows DR aggregators to participate in the reserve market in order to cope with renewable power production uncertainty.

The above problems are stochastically formulated to address the uncertainty of market prices as well as wind and PV power production. In addition, risk modelling is carried out using Conditional Value at Risk (CVaR). Each problem is rendered as a linear programming approach to be solved using General Algebraic Modelling System (GAMS), which is a commercially available optimization tool.
Declaration by author

This thesis is composed of my original work, and contains no material previously published or written by another person except where due reference has been made in the text. I have clearly stated the contribution by others to jointly-authored works that I have included in my thesis.

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To my beloved wife, Negar, my adorable parents and lovely family
# TABLE OF CONTENTS

ABSTRACT ................................................................................................................... II

TABLE OF CONTENTS ............................................................................................. XV

LIST OF FIGURES ...................................................................................................... XIX

LIST OF TABLES ........................................................................................................ XXI

ABBREVIATIONS ........................................................................................................ XXIII

Chapter 1  Introduction ............................................................................................... 1

1.1 Overview of Electricity Markets and Demand Response (DR) .................... 1

1.2 Motivation ............................................................................................................. 3

1.3 Thesis Objectives ................................................................................................. 5

1.4 Thesis Structure .................................................................................................. 6

Chapter 2  Literature Review .................................................................................... 9

2.1 Literature review .................................................................................................. 9

  2.1.1 Demand Response (DR) .............................................................................. 9

  2.1.2 Wind Power Offering and Application of DR by Wind Power Producers .... 13

  2.1.3 Electricity Retailers and Application of DR in Their Energy Plan .............. 15

  2.1.4 Application of DR by ISOs ......................................................................... 17

Chapter 3  A New Demand Response Framework ................................................. 21

3.1 Introduction ......................................................................................................... 21

3.2 Demand Response Framework ......................................................................... 22

  3.2.1 DR Options .................................................................................................. 23

  3.2.2 Fixed (Forward) DR Contracts ................................................................. 25

3.3 Flexible DR Agreements ..................................................................................... 25

3.4 The Proposed DR Framework from an Aggregator’s Perspective ................. 26
Chapter 4  Employing Demand Response by Wind Power Producers ..........................39

4.1. Introduction..............................................................................................................39
4.2. The Australian National Electricity Market vs. the Nordic market .......................40
4.3. Wind Offering Strategy in the Australian National Electricity Market ..................41
   4.3.1. The Proposed Two-Step Plan ........................................................................41
   4.3.2. Case Study .......................................................................................................46
4.4. The proposed offering strategy for the Nordic Market ...........................................55
   4.4.1. The Proposed Trading Plan ............................................................................55
   4.4.2. Case Study .......................................................................................................61
4.5. Summary ..................................................................................................................67
4.6. Nomenclature ..........................................................................................................68

Chapter 5  Modelling Demand Response Aggregator Behaviour in Wind Power Offering Strategy  .........................................................................................................................73

5.1. Introduction .............................................................................................................73
5.2. The Proposed Wind Offering Strategy ....................................................................74
   5.2.1. Framework .......................................................................................................74
   5.2.2. Market Model ..................................................................................................76
   5.2.3. Objective Function ..........................................................................................77
5.3. Linear Formulation ................................................. 79
5.4. Case Study .......................................................... 81
  5.4.1. Data Preparation and Assumptions ........................................ 81
  5.4.2. Numerical Results .............................................. 83
  5.4.3. Sensitivity Analysis ............................................. 88
5.5. Summary .............................................................. 91
5.6. Nomenclature ......................................................... 91

Chapter 6  Demand Response Application by Strategic Wind Power Producers .......... 95
  6.1 Introduction .......................................................... 95
  6.2 Strategic Wind offering ........................................... 96
    6.2.1 Framework ...................................................... 96
    6.2.2 Uncertainty Characterization .................................. 99
  6.3 Problem Formulation ............................................ 99
  6.4 Linear Formulation ............................................... 102
  6.5 Case Study .......................................................... 105
    6.5.1 Data Preparation and Assumptions .............................. 105
    6.5.2 Numerical Results .............................................. 107
    6.5.3 Imbalance Price Sensitivity Analysis .......................... 109
  6.6 Summary .............................................................. 111
  6.7 Nomenclature ......................................................... 112

Chapter 7  Employing Demand Response by Electricity Retailers ......................... 115
  7.1 Introduction .......................................................... 115
  7.2 Employing DR by Electricity Retailers .............................. 117
    7.2.1 Pool-Order Option .............................................. 117
    7.2.2 Spike-Order Option ............................................ 118
    7.2.3 Forward (Fixed) DR ............................................ 118

XVII
LIST OF FIGURES

Figure 1.1. Electricity market structure .............................................................................. 1
Figure 3.1. The proposed DR framework .............................................................................. 23
Figure 3.2. Structure of a typical DR option .......................................................................... 23
Figure 3.3. A trading DR framework for a DR aggregator ..................................................... 26
Figure 3.4. Reward-based DR curve ...................................................................................... 27
Figure 3.5. Load curve of Queensland on 9 January 2013 [127] ........................................... 30
Figure 3.6. A typical reward-based curve for the peak period ............................................. 32
Figure 3.7. TOU results ...................................................................................................... 33
Figure 3.8. Reward-Based DR results ................................................................................... 33
Figure 3.9. Impact of uncertain behaviour of consumers on DR outcomes ............................. 35
Figure 4.1. The proposed offering plan .................................................................................. 42
Figure 4.2. Expected profit for various number of scenarios .................................................. 47
Figure 4.3. Expected wind power production and spot prices .............................................. 48
Figure 4.4. The expected profit vs. standard deviation ........................................................ 49
Figure 4.5. The initial offer curves of step 1 .......................................................................... 51
Figure 4.6. The initial offer curve (S1) vs. the final offer curve (S2)- ρ =0 ............................... 52
Figure 4.7. The usage distribution of flexible DR in step 1 and 2- ρ =0 ................................ 52
Figure 4.8. DR options not exercised in step 2- ρ=0 ............................................................ 53
Figure 4.9. The initial offer curve (S1) vs. the final offer curve (S2)- ρ=5 .............................. 54
Figure 4.10. The usage distribution of flexible DR in step 1 and 2- ρ=5 ............................... 54
Figure 4.11. The proposed wind power offering strategy ..................................................... 55
Figure 4.12. Average wind power and spot price ................................................................. 61
Figure 4.13. The expected profit vs. the standard deviation .................................................. 63
Figure 4.14. The offers in the day-ahead market ................................................................... 63
Figure 4.15. Imbalance power for ρ = 0 .............................................................................. 65
Figure 4.16. Imbalance power for ρ = 1 .............................................................................. 65
Figure 4.17. Total power sold in the market for ρ = 0 and ρ = 1 ............................................. 66
Figure 4.18. The usage distribution of flexible DR 4 in step 1 and 2- ρ = 0 ........................... 67
Figure 4.19. The usage distribution of flexible DR 4 in step 1 and 2- ρ = 1 ........................... 67
Figure 5.1. The proposed bilevel wind offering strategy ..................................................... 75
Figure 5.2. Average wind power and spot price ................................................................. 82
Figure 5.3. Other competitors’ DR price scenarios ............................................................ 83

XIX
Figure 5.4. Expected profit vs. standard deviation for various risk levels ........................................ 84
Figure 5.5. Day-ahead market bids for the given risk levels .......................................................... 85
Figure 5.6. Balancing market participation for the given risk levels .................................................. 85
Figure 5.7. DR obtained by the wind power producer ........................................................................ 86
Figure 5.8. The DR price offered by the wind power producer ............................................................. 87
Figure 5.9. The total DR share traded with other players and the DA market ...................................... 88
Figure 5.10. Day-ahead offers by the risk-neutral wind power producer: Cases 1 and 2 .................. 89
Figure 5.11. Day-ahead offers by the risk-averse wind power producer: Cases 1 and 2 ................... 90
Figure 5.12. DR trading by the risk-averse wind power producer: Cases 1 and 2 ......................... 90
Figure 6.1. Strategic wind offering considering the DR aggregator behaviour .................................. 98
Figure 6.2. Wind power participation in the balancing market ......................................................... 108
Figure 6.3. DR sold to different DR purchasers ................................................................................ 109
Figure 6.4. Impact of imbalance price on wind power in the DA market ......................................... 110
Figure 6.5. Impact of imbalance price on demand scheduled in the DA market ............................. 111
Figure 7.1. Real-time prices of the Queensland region during January 2011 ............................... 116
Figure 7.2. The DR framework in the energy problem of a retailer ................................................. 117
Figure 7.3. The reward-based DR curve .......................................................................................... 119
Figure 7.4. The expected demand required by the retailer ............................................................... 125
Figure 7.5. Pool-order option prices ............................................................................................... 125
Figure 7.6. Spike-order option prices ............................................................................................. 126
Figure 7.7. The expected cost vs. standard deviation ...................................................................... 127
Figure 7.8. The share of each resource in total required energy by the retailer ............................... 128
Figure 7.9. The percentage of energy procured from each resource in summer ........................... 129
Figure 7.10. The percentage of energy procured from each resource in winter ............................ 130
Figure 8.1. Original vs. net load profile (SA, 14-22 Jan 2013) ....................................................... 138
Figure 8.2. Three bus system ......................................................................................................... 141
Figure 8.3. The cost of the system for various cases ...................................................................... 143
Figure 8.4. Load shedding in various cases ..................................................................................... 144
Figure 8.5. The scheduled power for power plants in the day-ahead market ............................... 147
Figure 8.6. The upward reserve for conventional power plants .................................................... 147
Figure 8.7. IEEE 24-bus System .................................................................................................. 149
Figure 8.8. The cost of the IEEE 24-bus system ............................................................................ 150
LIST OF TABLES

Table 3.1. Retail price tariffs in Queensland ................................................................. 31
Table 3.2. Elasticity matrix ......................................................................................... 31
Table 3.3. Fixed DR price ........................................................................................... 32
Table 3.4. Demand and price of DR options ............................................................... 32
Table 3.5. Fixed DR energy (kWh) ............................................................................. 34
Table 3.6. Exercise of DR options ............................................................................. 34
Table 4.1. DR contracts details ................................................................................... 49
Table 4.2. Fixed DR contracts .................................................................................... 50
Table 4.3. Signed DR options in step 1 .................................................................... 50
Table 4.4. Contracted flexible DR in step 1 (MWh) .................................................... 50
Table 4.5. DR contracts details ................................................................................... 62
Table 4.6. Fixed DR contracts .................................................................................... 64
Table 4.7. Signed European DR options in step 1 ...................................................... 64
Table 4.8. Contracted flexible DR in step 1 (MWh) .................................................... 64
Table 5.1. DR share of other competitors and the DA market (MWh) ......................... 88
Table 6.1. Offers by demand, generators and DR in the day-ahead market ............... 106
Table 6.2. Day-ahead market clearing price ................................................................ 107
Table 6.3. Energy Volume sold to the DA market by the WPP, GENCOs and the DR Aggregator (MWh) ........................................................................................................... 107
Table 6.4. DR price offered by the wind power producer .......................................... 109
Table 6.5. Impact of the imbalance price on the DA market price ($/MWh) ............... 110
Table 6.6. Impact of the imbalance price on the wind power participation in the balancing market (MWh) ........................................................................................................... 110
Table 6.7. Impact of the imbalance price on DR procurement by the wind power producer (MW, $/MWh) ........................................................................................................... 111
Table 7.1. Forward prices ($/MWh) .......................................................................... 126
Table 7.2. Forward DR prices ($/MWh) .................................................................... 126
Table 7.3. The percentage of each DR in total energy (%) ........................................ 128
Table 7.4. Exercised periods of pool-order options ................................................... 130
Table 7.5. Exercised periods of spike-order options ................................................... 130
Table 8.1. Generator data .......................................................................................... 141
Table 8.2. Wind and PV power scenarios (MW) ......................................................... 141
Table 8.3. Studied cases with various resources integration (%).................................142
Table 8.4. Wind spillage in different scenarios for the given cases (MW)..........................145
Table 8.5. Demand response in different scenarios for the given cases (MW) .......................146
Table 8.6. Wind power scheduled in the energy market (MW).......................................146
Table 8.7. Downward reserve from generator 2 (MW) ....................................................148
Table 8.8. Cases considered for study on the IEEE RTS 24-bus system..........................150
Table 8.9. Wind spillage for the IEEE RTS 24-bus system............................................151
Table 8.10. DR deployed in the reserve market for the IEEE RTS 24-bus system..................151
ABBREVIATIONS

ADRO  American Demand Response Option
AEMC  Australian Energy Market Commission
AEMO  Australian Energy Market Operator
ARIMA  Autoregressive Integrated Moving Average
CVaR  Conditional Value-at-Risk
DA  Day-ahead
DG  Distributed Generation
DISCO  Distribution Company
DR  Demand Response
DRO  Demand Response Option
DRX  Demand Response Exchange
DSM  Demand Side Management
EDRO  European Demand Response Option
EPEC  Equilibrium Problem with Equilibrium Constraints
FERC  Federal Energy Regulatory Commission
GAMS  General Algebraic Modelling System
GENCO  Generation Company
IEEE  Institute of Electrical and Electronics Engineers
ISO  Independent System Operator
KKT  Karush-Kuhn-Tucker
LSE  Load Serving Entity
MAPE  Mean Absolute Percentage Error
MISO  Midwest Independent System Operator
MO  Market Operator
MPEC  Mathematical Program with Equilibrium Constraints
NEM  National Electricity Market
NSW  New South Wales
NYISO  New York Independent System Operator
PAR  Peak-to-Average Ratio
PJM  Pennsylvania-New Jersey-Maryland
PO  Pool-Order Option
PV  Photovoltaic
QLD  Queensland
RET  Renewable Energy Target
Rho  Symbol representing \( \rho \)
SA  South Australia
SO  Spike-Order Option
TOU  Time-of-Use
TSO  Transmission System Operator
US  United States
VIC  Victoria
VOLL  Value of Lost Load
WPP  Wind Power Producer
Chapter 1

Introduction

1.1 Overview of Electricity Markets and Demand Response (DR)

Power system restructuring has enabled the emergence of electricity markets around the world. In the market environment, a single entity is no longer in charge. Multiple agents competitively interact to deliver energy to consumers. The structure of the new energy market is shown in Figure 1.1 [1].

![Electricity market structure diagram]

**Figure 1.1. Electricity market structure**

Agents participating in the electricity market are categorized as follows [1].

- Generation companies (GENCOs): along with their main duty, i.e. producing electricity and selling it to the market, they may also participate in other services such as regulation
and reserve for maintaining the quality and security of the electricity supply. A GENCO may sell energy to the electricity market and/or directly to consumers through bilateral contracts.

- Independent system operator (ISO): is a non-profit agent responsible for maintaining the security of the power system. The Independent System Operator must provide equal access to the grid for all consumers, retailers and producers.

- Market Operator (MO): is responsible for the economic management of the market. In addition, the market operator administers market rules and determines prices and quantities of energy traded in the market. In some markets, such as the Australian National Electricity Market (NEM), PJM and New England ISO markets, the functions performed by the ISO and the MO are carried out by a single entity [2]. In this case, the ISO (in Australia, Australian Energy Market Operator (AEMO) [3]) is in charge of market management.

- Regulator: is a government body responsible for ensuring the fair and efficient operation of the market.

- Transmission system operators (TSOs): own transmission assets such as high voltage lines, cables, transformers, etc.

- Distribution companies (DISCOs): own and operate distribution (low voltage and medium voltage) networks and are responsible for the operation, maintenance and development of the distribution network.

- Retailers: play an intermediary role in the market, where they buy energy from the wholesale market to sell it to end-users.

The electricity market has emphasized the importance of resource-efficiency of electricity production due to closer alignment between customers’ electricity prices and the value they place on electricity [4]. In addition, new challenges such as market price uncertainty, more intermittent power resources and the ability to exercise market power by some power plants have been introduced in electricity markets. These issues result in new solutions, where enhancing the demand side in order to encourage consumers to be more involved in the market is a key driver [4]. As a consequence, the so called “Demand Side Management (DSM)” concept which had been used before the restructuring of power systems was required to be amended to consider the unique features of electricity markets. DSM was therefore redefined and replaced by a new concept called Demand Response (DR), to be able to cope with new challenges in the market [5].

Demand Response (DR) is defined by the Federal Energy Regulatory Commission (FERC) of the United States as follows [5]. “Changes in electric usage by demand-side resources from their
normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized”. DR programs are basically classified either as time-based and/or incentive-based programs [6]. In time-based DR programs, customers change their usage patterns in response to the defined prices by utilities. Time-of-use, real-time pricing and critical peak pricing are well-known time-based DR actions. In incentive-based programs, customers reduce their load for a given period in response to the reward offered by utilities. Direct load control, interruptible load and emergency DR are common types in this group.

DR is becoming more important in facilitating the electricity market:

- to reduce wholesale power prices;
- to provide an efficient operation of markets;
- to enhance reliability and support the use of renewable energy resources [7].

Therefore, market regulators have been evaluating DR potential and seeking new ways to explore DR products in the market. For instance, Australian Ministerial Council on Energy has asked the Australian Energy Market Commission (AEMC) to facilitate an efficient Demand Side Participation (DSP) in the NEM. Consequently, a comprehensive investigation has been taken by the AEMC [8]. According to the AEMC report [8], it is estimated that load reduction is possible in three major states of Australia (NSW, QLD and VIC), which could be from 400 MW to over 1300 MW by 2020. This would lead to a cost saving of between $4.3 and $11.8 billion over the next ten years, which equates to 3-9% of total forecast expenditure on the supply side. FERC in the U.S estimated the demand response resource potential contribution from the U.S could be nearly 72,000 MW, or about 9.2 percent of U.S demand in 2012 [5]. Various DR programs have been practiced in different U.S markets, where load as a capacity resource, interruptible load, direct load control and time-of-use programs were the most successful ones.

1.2 Motivation

While advantages of demand response in electricity markets are well-recognized, there are still barriers to DR progress. An important barrier identified is the lack of customers’ engagement in DR programs. The FERC [5] in the U.S discusses this issue as follows. “Customers need to be effectively educated and informed about demand response and smart grid opportunities. Effective outreach and communication are needed to explain demand response, time-based pricing and smart grid investments and the impacts of these at the customer level”. In order to cope with this issue, there is a need for a market player responsible for engaging with customers to explore their DR potential. Such a player has recently evolved in some electricity markets and is known as a “DR
aggregator”. The DR aggregator applies various DR programs to electricity consumers and sells its outcome to the electricity market. The importance of the role of DR aggregators in the market has been emphasized in different countries. For instance, the AEMC in Australia has advised more active DR aggregators as a main solution in enhancing DR outcomes [8]. FERC also placed Order 719 in 2008, through which DR aggregators are required to be treated as similar to other generators in the wholesale market. Consequently, they can bid their DR products into the energy and ancillary services markets. This participation in the market has consequently been the focus of some investigations in very recent years [9-11]. Nevertheless, no work pays attention to bilateral DR contracts between a DR aggregator and DR purchasers. Investigation on these types of DR contracts is necessary since there are various market players such as wind power producers and electricity retailers, which seek DR through these contracts in order to cope with the uncertainty they are faced with.

Wind power is a leading renewable energy resource worldwide. This resource has been growing rapidly due to various supportive policies and subsidies established by governments around the world. Operation of wind power has almost matured in some countries such as Denmark and Germany, and it is expected that this will happen in other markets such as the Australian National Electricity Market (NEM) in the near future. As a result, wind power producers are expected to participate in the market like other power plants. They are required to place their offer into the market while being responsible for their power imbalance during real time. Note that this is the current practice in some markets such as Western Denmark [12]. This is indeed a challenging task for wind power producers since their power production is uncertain. Thus, they may have to compensate their power shortage in the real-time market, where there is a risk of price volatility in this market. As a solution for this issue, the coordination of wind power with controllable resources such as hydro and storage units is proposed [13-15]. DR is another important issue, which can be useful. In this way, wind power producers may need to procure DR from DR aggregators through bilateral DR contracts.

Electricity retailers are the major market players on the demand side. They procure energy from the market and sell it to electricity consumers. While their sale price to customers is usually set to a flat rate, they have to buy electricity in the pool market where its price is uncertain and in the worst cases, it may see huge spikes. In order to cope with price uncertainty, retailers usually procure part of their energy through bilateral contracts with generation companies [16-18]. Another way to alleviate price spikes could be using a suitable DR scheme. Therefore, electricity retailers may implement DR programs with consumers and/or procure DR products from DR aggregators.
Chapter 1. Introduction

As previously mentioned, ISOs are in charge of maintaining the security of the market. This has become a challenging issue due to the integration of renewable energy resources. Wind power, usually in a large scale is uncertain. On the other hand, solar power is variable and it mostly comes in small-scale systems such as roof-top PV. The variability of PV power is indeed worse than wind power since this resource is on the demand side and is beyond the control of the ISO. The uncertainty associated with wind and PV power may require the ISO to procure more reserve resources, which is mostly provided by conventional power plants. DR is another beneficial resource which is usually fast enough to provide reserve products. Therefore, the ISO may need to encourage DR aggregators to participate in the reserve market and sell their DR product to this market.

1.3 Thesis Objectives

The objectives of this thesis are to:

- propose a demand response framework through which DR is traded as a public good between a DR purchaser and a DR aggregator. Various DR contracts with unique features are proposed and formulated for this purpose.

- investigate the proposed DR framework applicability in offering strategies by wind power producers in two markets, the Australian NEM and the Nordic Market.

- address DR aggregator behaviour in DR employment by wind power producers. In this way, a wind power producer has to compete with other DR purchasers as well as electricity markets to obtain its required DR from a DR aggregator.

- analyse the application of DR by wind power producers owning a significant amount of wind power production. A strategic wind power producer with the ability of exercising market power in day-ahead markets is modelled in such a way that the producer can use DR to cope with power production and imbalance price deviations.

- investigate how DR can be useful for electricity retailers. An energy procurement plan is proposed and formulated for a retailer in which the retailer is able to procure DR through the proposed DR framework in order to lessen its risk of facing uncertain pool prices.

- finally, evaluate the application of DR by an ISO. The ISO allows DR aggregators to participate in the reserve market in order to cope with the uncertainties of wind power on the supply side and roof-top PV power on the demand side.
1.4 Thesis Structure

The thesis is structured as follows.

Chapter 2 reviews the relevant work to this thesis research. A comprehensive review of demand response and its applications for electricity markets is provided. Wind offering strategy and the solutions to ease wind power uncertainty are addressed next. Then, a review of studies on electricity retailers’ issues is delivered. Finally, investigations on using DR by ISOs are reviewed.

Chapter 3 discusses the proposed demand response framework. DR contracts are explained and formulated in this chapter. In addition, a case study is presented to show the validity of the proposed DR framework from a DR aggregator point of view.

Chapter 4 investigates the application of DR by wind power producers. Two well-known markets are considered: the Australian National Electricity Market (NEM) and the Nordic Market. A proper wind offering strategy for each market is proposed in such a way that a wind power producer is able to employ DR through the proposed DR contracts. This strategy is evaluated using the realistic data of each market.

Chapter 5 presents studies on the behaviour of a DR aggregator in wind offering strategy. To this end, a bilevel problem is proposed in which the upper level addresses the wind offering strategy while the lower-level model formulates the DR aggregator behaviour. This behaviour is modelled in such a way that the DR aggregator is able to sell its DR product to the wind power producer, other market players interested in buying DR and the electricity market. The bilevel model is transformed into a single-level linear programming approach using proper techniques and is evaluated on a realistic case of the Nordic market.

Chapter 6 provides assessments on DR application by a strategic wind power producer, which is able to exercise market power to alter market prices. For this purpose, a bilevel model including one leader and two followers is proposed. The upper-level problem is the offering strategy by the strategic wind power producer. The lower-level problem 1 represents the market clearing through a social welfare maximization model. DR is considered in the lower-level problem 2, where the DR aggregator behaviour is modelled similarly to Chapter 5.

In Chapter 7 DR applications by an electricity retailer is investigated. The electricity retailer is allowed to procure DR through setting DR contracts with DR aggregators and also implementing reward-based DR with consumers. An energy procurement plan is proposed in which the retailer uses DR in addition to the commonly used pool market and forward contracts. The problem is evaluated for a realistic case of Australia and results are presented.

Chapter 8 provides formulations of an energy and reserve co-optimization model by an ISO. The ISO allows DR aggregators to participate in the reserve market and hence, it will be able to manage
the uncertainties of wind power on the supply side and roof-top PV power on the demand side through the reserve market. The study assesses the impact of increasing wind and PV power levels in the network and shows the effectiveness of using DR to ease this issue. A simplified three-bus power system is studied to understand the approach and then the IEEE 24-bus system is used to show the validity of the proposed approach.

Chapter 9 provides summary findings of the thesis and concludes the main contributions. In addition, possible future research is recommended in this chapter.
Chapter 2
Literature Review

This chapter provides a comprehensive literature review on the relevant work to this thesis research. First, a review of DR programs, their integration in electricity markets and experience in some leading markets is addressed. Then, investigations on wind offering strategies as well as the proposed solutions for alleviating the risk of wind power producers in electricity markets are delivered. In addition, studies on using DR in wind offering strategies are reviewed. After that, a review of DR applications by electricity retailers is given. Finally, relevant studies on how DR can be useful in electricity markets with high penetration of wind and PV power are presented in the last section. Note that in each section, the contributions made by this thesis are also highlighted.

2.1 Literature review

2.1.1 Demand Response (DR)

Numerous studies have addressed DR issues in recent years. In specific, these investigations are classified in two groups. The first group explains DR basics, various DR programs and technical DR implemented with consumers. The second group is mainly relevant to bringing DR into electricity markets.

In line with DR programs in detail, the following investigations are provided. The definition of DR programs is addressed in [6]. This work introduces various DR programs and categorizes them into two groups, namely incentive and price-based DR. In addition, customers’ response is represented in three actions: first, load shifting by customers as a result of high prices; secondly, reducing electricity usage in peak periods without changing the load pattern in other periods; thirdly, using on-site distributed generation. Elasticity reflects the responsiveness of customers to price changes. This concept is discussed in [19, 20]. Reference [19] discusses self and cross
elasticity based on consumers behaviour in responding to pool price changes. In addition, the impact of elasticity on market prices is evaluated. The authors in [20] further extend this work, where it elaborates the challenges with demand side activities and presents new solutions for them.

Incentive-based DR programs are formulated in several investigations such as [21-23]. Reference [21] provides the mathematical formulations of two incentive-based DR programs, i.e. interruptible load services and capacity market programs. An economic model is derived for this purpose in which the impacts of incentives and penalties in the given DR programs are evaluated according to different objectives such as peak reduction, energy reduction and load factor improvement. A coupon-based method is formulated in [22] where the incentive offered to consumers is determined according to market prices. A load serving entity offers consumers a voluntary coupon incentive along with the existing flat rate electricity charge through which consumers reduce their usage during price spikes. An incentive-based scheme is presented in [23] through which both energy cost and peak-to-average ratio are minimized using a game theory approach. Consumers can benefit from two-way communication infrastructures to manage their energy consumption according to the prices offered by utilities.

Price-based DR actions are also presented in some research such as [24-26]. The authors in [24] propose a mathematical model for flexible price elasticity of demand to calculate the elasticity of each demand response program based on the electricity price before and after implementing that program. Paper [25] models a real-time pricing approach for smart grid applications. A robust programming approach is formulated in which a consumer maximizes its utility by adjusting its consumption in advance based on the market price. A comprehensive time-of-use model is formulated in [26] where the elasticity is considered as a non-zero cross and flexible function.

Control strategies of managing electrical loads such as water heater systems, air conditioners, space heating and cooling systems are provided in [27-32]. In [27] a direct load control program is proposed in which air-conditioning systems are controlled as an aggregated load and as a result, the load shape of peak periods can be effectively reshaped. In a stochastic approach, [28] presents an objective function expressing comfort/cost trade-offs for household residents. In this model air-conditioning systems are controlled in such a way that they permit the controller to respond to both energy prices and randomly varying environmental conditions. In a pilot project in the PJM market, [29] estimates the water heater control strategies for electricity consumers. The authors in [30] present physical models of different residential appliances such as water heater, space cooling/heating, clothes drying and electric vehicles, which are aggregated using a stochastic method to create controllable load profiles of a distribution feeder. The coordination of demand response and storage units is investigated in [31, 32].
With regards to the modelling of DR in electricity markets, many studies have been published. In a perfect statement, FERC identified DR applications in its ruling in 2008 [7]: “Demand response can provide competitive pressure to reduce wholesale power prices; increases awareness of energy usage; provides for more efficient operation of markets; mitigates market power; enhances reliability; and in combination with certain new technologies, can support the use of renewable energy resources, distributed generation and advanced metering. Thus, enabling demand-side resources, as well as supply-side resources, improves the economic operation of electric power markets by aligning prices more closely with the value customers place on electric power”. The authors in [33] identify the responsibilities of different organizations, known as load serving entities, independent system operator (ISO) and regulators, for promoting DR. The authors in [9] list various DR programs which are available in U.S markets. These programs range from voluntary to mandatory actions in which DR providers can participate in different markets, i.e. energy, reserve and capacity markets. A bidding strategy method for day-ahead markets is developed in [34] considering DR programs. Air conditioning is taken into account in order to evaluate the impact of responsive consumers on demand bidding. A day-ahead market-clearing price is proposed in [35] where price-responsive consumers can bid in the market. A load participation factor is developed to show the responsiveness of consumers. A new model for responsive loads is proposed in [36], where the operating constraints of loads including bids, hourly profiles, and inter-temporal characteristics are considered in their bidding into the market. A security constrained unit commitment is formulated from an ISO’s point of view in which the impacts of DR on constrained power systems are evaluated. A DR aggregator is modelled in [10], where it is able to participate in the energy market while scheduling different DR programs such as load curtailment, load shifting and onsite generation for consumers. This model is further developed in [11], where customers’ characteristics are considered in a hierarchical DR model. A unit commitment problem is proposed in [37], where an ISO determines the DR quantity and the incentive paid to DR participants in the market.

A new market, called demand response exchange (DRX), is proposed in [38, 39]. The proposed market is pool-based in which DR is traded between DR sellers and buyers. A DRX operator is modelled which is responsible for clearing the DRX market by receiving offers and bids from DR sellers and buyers. This model is improved in [40] by modelling Walrasian auctions, where in an iterative way, DR players update their DR quantity bids in response to the prices adjusted by the market operator. This is repeated until market equilibrium is obtained at the Pareto optimal.
Chapter 2. Literature Review

DR is a useful resource in providing ancillary services. The authors in [41] present a security constrained unit commitment by an ISO through which DR aggregators provide capacity services in a reserve market. DR aggregators submit two sets of offers in the reserve market, i.e. a capacity cost and an energy cost of reserve, which the latter is paid if the reserve is deployed by the ISO. In [42], a smart micro-grid operator is proposed as a reserve provider. This operator on one hand controls its internal load through price signals and on the other hand interacts with an ISO to obtain requests for reserve. DR is employed in [43] as a frequency restoration resource during contingencies. An adaptive control plan is proposed in which an emergency DR program is applied along with spinning reserve to bring frequency to the pre-disturbance level. Reference [44] proposes a method for integrating responsive loads in spinning reserve markets and evaluates the flexibility that these loads provide for these markets.

There are some reports representing the experience of DR around the world. For instance, experience of implementing DR programs in the PJM market and New York Independent System Operator (NYISO) is addressed in [45] and that of European markets is summarized in [46]. In Australia, DR has been identified as a critical factor in the future management and operation of the electricity market and a target of additional 5% reduction (2,800 MW) in system peak by 2025 has been set [47].

The main contribution of this thesis in DR programs is as follows [48-52].

- This thesis proposes a DR framework in which DR is considered as a public good and accordingly, a DR aggregator is able to trade it with DR purchasers through various contracts. The proposed contracts are fixed DR, flexible DR and DR options, where each has unique features which are addressed through mathematical formulations. Fixed DR contracts are set at a certain price and volume for a future period. Flexible DR agreements allow a DR buyer to set the contract in advance and change its usage distribution over the contract period in real time. DR options are signed in advance, but a DR buyer has the right not to exercise them during the delivery time. DR options are designed in such a way that they can be used in normal pool price fluctuations (pool-order options), spike price situations (spike-order options), exercised at any time before the expiration date (American DR options), and exercised at the expiration date (European DR options).
2.1.2 Wind Power Offering and Application of DR by Wind Power Producers

The main challenge with wind power producers is their production uncertainty. Two main solutions are provided in the literature to ease this issue. 1) Wind participation in short-term markets and proposing an optimal offering strategy for this purpose; 2) Coordination of wind power producers with controllable resources.

Optimal trading strategies are addressed in some investigations such as [53-64]. A stochastic model is presented in [53], where a wind power producer places its offer into the market while taking into account the uncertainty of wind production and market prices. The authors in [54] propose a base load contract for reducing the risk of facing uncertainty by a wind power producer. With the aim of minimizing the imbalance cost, a stochastic wind power offering plan is provided in [55]. The forecast error of power production is added to the actual production and then this is offered in the market. Reference [56] determines the energy level contracted in a market with three floors, i.e. day-ahead, adjustment and balancing markets. A multistage stochastic approach is formulated in which the wind power producer offers in the day-ahead market, corrects its day-ahead quantity in the adjustment markets and finally clears deviations in the balancing market. A joint energy and bilateral reserve market model for trading wind power has been proposed in [57], where it allows wind power producers to model their production uncertainties as well as other competitors behaviour in their bidding strategy. The authors in [58] evaluate the profitability of wind power producers in enrolling in frequency regulation, particularly in a secondary regulation market. Wind power offering under the uncertainty of locational marginal prices is assessed in [59], where offers for various risk levels as well as production deviation penalties are derived and compared. An agent-based wind offering strategy is proposed in [60], where it is shown that a wind power producer can increase its profit by improving power forecasts as well as using learning algorithms. A predictive distribution model is presented in [61] to increase the accuracy of wind power offering in the market. A risk-constrained offering model is provided in [62], where a wind power producer takes into account its operational costs in its offering strategy. The penalty of wind power forecast errors in wind offering is evaluated in [63]. In addition, a new model is presented to capture the distribution of these errors. Offering strategies based on forecast models and stochastic approaches are evaluated in [64]. This work shows the advantages of stochastic models over forecast techniques, and also highlights the importance of adjustment markets for wind power producers.

Joint operation strategies are presented in several studies [13-15, 65-72]. A predictive control system is proposed in [13] to provide an enhanced wind and battery energy storage systems.
dispatch. A two-stage stochastic programming approach is proposed in [14], which addresses the co-offering of wind and pump-storage units considering the random scenarios of wind power production and market prices. The authors in [15] investigate the joint operation of wind and pump-storage units considering intra-hour wind power variations. The joint operation of wind and battery is studied in [65], where sizing and control methodologies for a zinc–bromine flow battery-based energy storage system is derived. A price-based unit commitment is formulated in [66] to address the coordination of wind and hydro units. Reference [67] proposes a method for joint operation of wind and pump-storage plants in day-ahead and ancillary services markets. The impact of wind and hydro coordination on a high integration of wind in island systems is evaluated in [68]. The authors in [69] evaluate the bidding strategy of wind and hydro in various scenarios, i.e. wind and hydro joint bidding, separate bidding, with physical and without physical connection. A new method based on the Shapley value is presented in [70], which helps wind and hydro units fairly share their joint offering profit. A risk-constrained trading of wind and thermal units is proposed in [71], where the optimal trade-off between the expected profit and risk is derived. A stochastic offering method for a virtual power plant owning wind and storage systems is presented in [72].

Demand response (DR) is another source, which can be used in a joint operation with wind power producers. Relevant studies mostly provide the joint operation of DR and wind power producers to improve network and market operations [73-75]. Few papers investigate DR applicability from wind power producers’ point of view [76-78]. The authors in [76] propose a method in which a virtual power plant is modelled to coordinate wind power and demand response. They model the offering of the virtual power plant in day-ahead and balancing markets. An intraday demand response exchange is proposed in [77], where a wind power producer can buy DR from this market in order to alleviate its power production deviation in the real-time market. A decision framework is proposed in [78], where a wind power producer forecasts its production and accordingly uses demand response to mitigate possible deviations.

A few papers have recently raised the issue of market power capability by wind power producers [12, 79-82]. Reference [79] is the most recent and comprehensive one of these. The authors investigate the high penetration of wind power for a wind power producer by modelling it as a strategic player in both day-ahead and balancing markets. An equilibrium problem with equilibrium constraints (EPEC) is formulated. The authors in [12] consider a wind power producer which is a price maker in the day-ahead market and a deviator in the balancing market. Unlike [12], a wind power producer in [80] is fully competitive in the day-ahead market while having market power in
the balancing market. The authors in [81] investigate the effect of a price-maker wind power producer on the market price. A study of the Nordic market in [82] indicates that producers with fluctuating production may act strategically in their bidding on the spot market due to the asymmetric cost of the regulating market.

The contributions of this thesis regarding wind offering strategies are as follows.

- **New wind offering strategies are proposed for the Australian National Electricity Market (NEM) and the Nordic market, in which a wind power producer in these markets is able to procure DR through the proposed DR framework in a two-step plans [51, 52].**

- **The behaviour of a DR aggregator is modelled in DR application by a wind power producer. To this end, a bilevel problem is proposed in which the upper level problem represents wind offering and the lower-level problem models the DR aggregator behaviour. In this way, the DR aggregator is able to competitively sell its DR product to the wind power producer, other market players and the electricity market [83].**

- **DR application is evaluated by a strategic wind power producer, which has the ability to exercise market power. A bilevel approach including one leader and two followers is formulated for this purpose. The strategic wind power producer behaviour is presented in the upper level and lower-level 1. The lower-level 2 addresses the DR aggregator behaviour [84].**

### 2.1.3 Electricity Retailers and Application of DR in Their Energy Plan

Electricity retailers buy energy from electricity markets to sell to consumers. Therefore, they have to consider two main tasks: procuring energy from different markets while managing pool price violations and attracting more consumers through offering competitive electricity sale prices. Several investigations are provided to deliver the above issues [16-18, 85-91]. Carrion et al [16] propose a yearly framework to decide the forward contracts which retailers should sign and to determine the selling price offered to consumers. For this purpose, risk-constrained stochastic programming is proposed. Uncertainties of pool prices and client demand are modelled through time-series models. In addition, a piecewise price quota is considered to take into account the rival retailers’ competition, as well as CVaR for risk modelling. This approach is extended to a bilevel model in [85] to take into account retailers’ competition. Thus, the action of the follower (the amount of energy purchased by clients) affects the decision plan of the leader (the retailer).
Call option contracts and self-production are utilized as energy procurement sources in [17], where mixed-integer stochastic programming is proposed to calculate the retailer’s involvement in each supplying source, as well as the sale price. Also, a market share function is presented to take into account the competition among retailers. The authors in [86] use interruptible loads for managing the risk of pool markets faced by a load serving entity (LSE). It is assumed that the LSE procures its energy from bilateral contracts and pool markets. In price spike situations, the LSE uses interruptible load to mitigate its exposure to high market prices. The concept introduced in [17, 86] is further extended in [18] where the selling price offered to consumers is defined based on time-of-use tariffs. Electricity selling price is determined in [87] using a capital asset pricing model. Also, risk adjusted recovery on capital (RAROC) is used to quantify the risk of the pool. A technical-economic model is proposed in [88] to determine the selling price offered to consumers. The impacts of different price strategies, discount on tariffs and the customer’s elasticity are investigated on the retailer’s profit. The authors in [89] present a two-stage model in which day-ahead and hour-ahead markets, as well as DGs are considered for energy procurement by retailers. Short-term decisions of distribution companies (DISCOs) are made in the presence of DG and interruptible load options in day-ahead markets. The impact of uncertainty modelling on a retailer’s contract portfolio is investigated in [90] where the benefit of incorporating the correlation between load and price into an energy procurement model is the insight result. Bilateral contracts are evaluated in a risk-constrained energy procurement methodology for electricity retailers [91]. A modified model is presented where competition among retailers is considered by introducing a switching load consumers’ scheme. Also, the risk is modelled using RAROC.

DR is a useful resource for hedging the risk of retailers. A few papers address this concept [86, 92-100]. The authors in [86] use interruptible loads to alleviate the uncertainty of pool markets faced by a load serving entity. Two interruptible load contracts, pay-in-advance and pay-as-you-go, are evaluated in [92] as the energy resources of electricity retailers. Self-production is also used in [93] to limit the risk of cost fluctuations in pool markets. Reference [94] uses interruptible loads as an energy resource of distribution companies. A short-term deterministic model is presented in [95], in which distribution companies can use interruptible loads to place bids in the market. Besides interruptible loads, real-time pricing and time-of-use are also offered by distribution companies to alter the energy usage of consumers [96]. With the aim of reducing the energy bought from pool markets, [97] proposes a time of use pricing scheme through which a retailer can apply this program to consumers. The authors in [98] investigate the impact of real-time pricing on reducing the risk of retailers. A cost minimization problem is proposed in [99], where a retailer uses demand response to
avoid cost fluctuations in the market. Peak clipping and load shifting programs are implemented with consumers to reduce their load during peak prices. A bilevel problem is presented in [100], where consumers, in the lower-level problem, respond to dynamic prices provided by a retailer as the leader.

This thesis contributes in this area as follows [49, 50].
- *The proposed DR framework in section 2.1.1 is applied to the energy procurement problem of an electricity retailer. A stochastic cost function is proposed through which the retailer uses DR in addition to the commonly used pool market and forward contracts. In addition, the uncertainty of pool prices is addressed using their plausible scenarios.*

### 2.1.4 Application of DR by ISOs

A major task for ISOs is to maintain the security of the market. A high penetration of renewable resources brings some challenges to electricity markets. Wind power, usually on a large scale, is uncertain and non-dispatchable. The good thing however is that as wind penetration becomes significant, it is expected to be treated as similar to conventional power plants. Therefore, wind power producers have to participate in the market while compensating their power imbalances [12, 101]. This observation is not valid for PV power, where it is usually on the demand side. Indeed, PV power imposes uncertainty to demand, which causes more difficulties in the market dispatch carried out by ISOs.

Investigations are underway to resolve the above issues. A review of the literature indicates the majority of the study is dedicated to wind related problems and their proposed solutions. The reserve requirement for a system integrating wind power production is addressed in [102]. Pool pricing for such a system is presented in [103]. The joint operation of wind and controllable resources such as pump-storage systems, hydro power plants and battery storage units is provided as a solution for alleviating wind intermittency [104-109]. The authors in [104] assess the level of wind penetration in the Portuguese system while using flexible backup production. Storage systems are used to cope with wind curtailment during excess generation. A robust unit commitment is formulated in [105], which models the worst-case wind power output scenario and tries to compensate for it by using pump-storage units. The application of different storage technologies for the Dutch system with high wind integration is evaluated in [107]. A security constrained unit commitment is formulated in [108], where the dispatch-ability of wind power
producers is enhanced using pump-storage hydro systems. This problem is addressed using transmission-constrained systems in [109]. Correlation analysis of wind and hydro power plants is provided in [110], through which a system operator can develop wind based on hydro availability as well as load and price variations.

DR is also applied as a solution for easing wind power variability by ISOs [74, 75, 111-117]. References [74, 75, 111, 115] indicate that applying real-time pricing schemes results in a higher utilization of wind power production and a lower cost to the system. The authors in [112] evaluate the impact of DR on the generation mix of a system integrating wind power. A robust optimization model is presented in [113], where an ISO uses DR as a reserve provider to cope with wind power variability. DR is modelled using an uncertain price-elastic demand curve and its validity to accommodate wind power uncertainty is assessed. The impact of proper allocation of DR in a system integrating wind power is addressed in [114]. The authors in [116] propose a model to determine the load shifting level which an ISO needs to obtain from incentive-based DR programs to increase wind utilization and enhance transmission congestion. Time of Use pricing is used in [117] which is able to control electric water heaters in order to provide balancing reserve in a system with high penetration of wind power production.

The studies on PV are not as many as that of wind incorporation. Relevant studies mostly consider managing roof-top PV in distribution networks. For instance, references [118-120] study the impact of storage systems to mitigate PV fluctuations in low-voltage systems. A few investigations bring PV power plants into electricity markets, where they mostly seek how these power plants can participate in the market [121-123]. An energy management strategy (EMS) is proposed in [121], where PV power plants employ storage units through this strategy to mitigate their power fluctuations and accordingly, participate in electricity markets. A model for participating concentrating solar power in the market is proposed in [122], where a unit can use storage to increase its revenue. Economic impacts of solar power on the PJM electricity market are analysed in [123].

The thesis contribution on this section comes below [124].

- There is no investigation in which an ISO explicitly models a system integrating both PV (small units) and wind power production while employing DR for easing their intermittency. This thesis studies the challenging integration of these resources faced by an ISO. The uncertainties of wind power on the supply side and PV power on the demand side are modelled in an energy and reserve co-optimization model by the ISO. In
addition, the benefit of participating DR aggregators in the reserve market is investigated.

The next chapter will present the proposed DR framework. All the DR contracts will be explained and a case study is delivered to show the feasibility of using DR by a DR aggregator.
Chapter 3

A New Demand Response Framework

3.1 Introduction

Demand Response (DR) is defined as modifying the load profiles of electricity customers via offering incentives or establishing new price tariffs [6]. The key drivers of these programs comprise network and market issues. While maintaining the security and reliability of the network is the primary goal of the network-driven DR, alleviating the risk of pool price volatility is known as the main reason for employing market-driven programs [125].

DR is still at small scale in electricity markets. Many challenges such as customers’ unwillingness to participate in DR, lack of enough knowledge and training, lack of proper metering facilities (smart metering), as well as market barriers such as market policies are the key reasons. In addition, DR purchasers such as wind power producers, retailers and market operators are reluctant to contact every single electricity consumer to obtain DR. They prefer to buy DR products from a third-party company. In this way, DR is considered as a public good, which is traded between these

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1 This chapter has materials from the following references published by the PhD candidate.

**Proposed DR contracts are explained in:**


**Reward-based DR program is proposed in:**


**DR framework from a DR aggregator viewpoint is addressed in:**

companies and the third-party company. DR aggregators are such companies that are able to implement various DR programs with consumers to sell the outcome to DR purchasers.

A few papers in the literature address this topic. The authors in [38] propose a new DR market, which allows aggregators to sell their product through a pool-based market. A hierarchical market model is developed in [126], where aggregators are considered as a broker between residential end users and the market operator. With the aim of maximizing social welfare, the authors in [127] propose a decomposition algorithm to ease the implementation of DR by aggregators.

While the above studies focus mostly on participating DR aggregators in the market, there is no significant work which addresses the bilateral contracts between DR aggregators and DR purchasers. This chapter proposes a new Demand Response (DR) framework in which various DR contracts are proposed through which DR purchasers can bilaterally trade DR with a DR aggregator.

The structure of the chapter is as follows. First, the developed DR framework is discussed. Then, each DR contract is explained and relevant mathematical formulations are derived. In addition, a simple case study from a DR aggregator’s perspective is simulated and the results are analysed. Finally, the nomenclature section in the end of the chapter defines all variables, constants and numbers.

3.2 Demand Response Framework

The proposed DR framework arranges mutually attractive deals between DR purchasers and a DR aggregator. It is assumed that the DR aggregator is willing to bilaterally trade DR with these purchasers. The proposed DR framework is depicted in Figure 3.1. As can be seen, DR is traded through three main contracts: **DR options**, **fixed DR contracts** and **flexible DR agreements**. Note that double ended arrows indicate that DR flow can be either from the aggregator to DR purchasers or in the opposite direction. That is, the DR aggregator sells DR products to purchasers in specific periods, mainly peak periods. On the other hand it is also able to buy energy from them through DR agreements, where in this situation it can encourage electricity consumers to consume more energy. This usually happens during off-peak periods.
Each DR contract is discussed in the following subsections.

### 3.2.1 DR Options

A DR purchaser can arrange DR options with DR aggregators. Each DR option is determined with a specific offer including a certain volume and price for a given period. According to this contract, a DR purchaser has a right but not an obligation to purchase DR. This means that the purchaser signs this contract at the beginning of the decision time horizon. However, exercising the contract at the energy delivery time depends on whether it is profitable or not. If the contract is not carried through in real time, the DR purchaser has to pay a predetermined fee to the DR aggregator as the penalty of not exercising the contract. Figure 3.2 shows the structure of a typical DR option.
The cost of a DR option that a DR purchaser has to pay to the DR aggregator is formulated as follows.

\[
C_{o}^{DRO}(t) = P_{o}(t)A_{o}(t)v_{o}(t)d(t) + (1-v_{o}(t))f_{o}^{pen}(t), \quad \forall t, o
\]  (3.1)

Equation (3.1) consists of two terms addressing the cost of practicing the DR option by the DR purchaser and the penalty of not exercising the signed DR option. Binary variable \(v_{o}(t)\) indicates whether the contract is exercised or not. \(v_{o}(t)\) equal to 1 shows that the DR option \(o\) is used in real time. Otherwise, it states that the contract is not exercised and thus the DR purchaser has to pay \(f_{o}^{pen}(t)\) as the penalty of not exercising the DR option during time \(t\).

DR options can be categorized in four classes based on their applications. The first two are more suitable for the proposed two-step wind energy offering strategy which is presented in Chapter 4. The last two options are used for an energy procurement problem of electricity retailers which is presented in Chapter 7.

1- Type 1 is called European DR options (EDRO). Once the contract is set, both parties (DR purchaser and DR aggregator) agree on an expiration time. This expiration time is the only time that the agreed DR option can be exercised. Thus, the DR purchaser is not allowed to practice this contract at any other time, whether sooner or later than the set time.

2- In type 2 the DR option can be exercised at any time before the expiration time. This is similar to the well-known financial American-based options. Accordingly, we call it the American DR option. This adds an extra constraint, shown in (3.2), to the DR option cost formulated above. This expression indicates the period horizon \((t \in T_{ao})\) in which the American DR option \(ao\) can be exercised.

\[
\sum_{t \in T_{ao}} v_{ao}(t) \leq 1; \quad \forall ao = 1, 2, \ldots, N_{ao}
\]  (3.2)

3- A pool-order DR option is proposed in order to alleviate the risk of normal price fluctuations in the pool market. Consequently, risk-averse DR purchasers such as conservative retailers can procure part of their energy from DR instead of the uncertain pool market.

4- The pool market may face price spikes due to some circumstances such as high demand requirements on very hot summer days, transmission network congestion and failure in power system components. For instance, while the average pool price in the Australian National Electricity Market was $43/MWh in 2012, in the worst case of the year the price spiked as high as
$2892/MWh [128]. A spike-order option agreement is proposed as a way to limit the huge cost faced by DR purchasers, particularly retailers, during high price periods. This option is similar to the pool-order option except that the negotiated price is determined according to price spikes.

### 3.2.2 Fixed (Forward) DR Contracts

A fixed contract is an agreement between a buyer and a seller of an asset to be traded in the future [129]. Considering this concept, a fixed DR contract is proposed here, through which a DR purchaser buys this contract from a DR aggregator. It is assumed that the purchaser directly negotiates with the DR aggregator for a mutually attractive deal. Fixed DR contracts are offered in various blocks in which each block involves a certain amount of DR and price for a given period.

\[
\begin{align*}
C_{f,b}^{FDR} (t) &= P_{f,b}^{DR} (t) \times \lambda_{f,b}^{DR} (t) \times d(t) \\
&= \lambda_{f,b}^{DR} (t) \times d(t) \\
f &= 1, ..., N_{FDR}, \ b &= 1, ..., N_{BDR} \\
P_{f,b}^{DR,MIN} (t) \leq P_{f,b}^{DR} (t) \leq P_{f,b}^{DR,MAX} (t)
\end{align*}
\]

Expression (3.3) refers to the cost of the bth block of fixed DR f. In addition, the size of each contract’s block is restricted by (3.4).

### 3.3 Flexible DR Agreements

Flexible DR agreements give the DR buyer a chance to better utilize DR according to its real-time requirement. When the DR buyer and the DR aggregator arrange this contract, they negotiate the size, price and the duration of the agreement. However, during the delivery time the DR buyer has flexibility to manage the usage distribution of the contracted DR volume in the given period. That is, the DR purchaser is able to distribute the DR usage over the contract period to fulfil its requirement.

The cost of the flexible DR agreement is provided in (3.5). \(P_{flex}^{DR} (t)\) and \(\lambda_{flex}^{DR} (t)\) are the power and the price of flexible DR flex, respectively. The size of flexible DR is imposed in (3.6). Equation (3.7) is valid during the real time, where it states that the flexible DR volume over the contract period \(t \rightarrow SP; EP\) must be equal to the agreed volume \(E_{flex}^{Agrd}\) which was negotiated once the contract was set. \(SP\) and \(EP\) represent the start and the end of the contract period, respectively.

\[
C_{flex}^{FlexDR} (t) = P_{flex}^{DR} (t) \times \lambda_{flex}^{DR} (t) \times d(t) \\
flex = 1, ..., N_{flex}
\]
Chapter 3. A New Demand Response Framework

\[ P_{\text{flex}, \text{MIN}}(t) \leq P_{\text{flex}}(t) \leq P_{\text{flex}, \text{MAX}}(t) \]  
(3.6)

\[ \sum_{t=SP}^{EP} P_{\text{flex}}(t) \times d(t) = E_{\text{Agrd}}^{\text{flex}} \]  
(3.7)

### 3.4 The Proposed DR Framework from an Aggregator’s Perspective

This section analyses the proposed DR framework for a DR aggregator. The DR aggregator acquires DR by implementing time-of-use (TOU) and reward-based DR programs with consumers. The behaviour of consumers in the TOU program is modelled through elasticity factors, while in the reward-based DR it is demonstrated using uncertainty characterization. The obtained DR is then sold to purchasers through two proposed contracts, i.e. fixed DR contract and DR options.

The proposed DR trading framework is given in Figure 3.3. Electricity consumers include industrial, commercial and residential sectors. Each sector is offered a unique time-of-use tariff and a distinctive reward-based DR. The aggregator trades the DR product with purchasers through fixed DR contracts and DR option agreements. Note that double-sided arrows indicate that the energy flow can be either from consumers to DR purchasers or in the opposite direction.

![Figure 3.3. A trading DR framework for a DR aggregator](image)

The following subsections present the given trading framework in detail where the mathematical formulations of Time-of-use (TOU) and reward-based programs as well as the overall problem are presented. Finally, a case study for the DR aggregator is simulated and the results are analysed.
Chapter 3. A New Demand Response Framework

3.4.1 Time-of-Use program

Time-of-use (TOU) programs are well-known in the power industry. According to this program, consumers receive distinct price tariffs for a day, for example peak and off-peak tariffs. Consequently, they manage their electricity usage depending on how elastic they are to price changes. If they are highly elastic, the response is high and vice versa.

The energy obtained from the TOU program is formulated in (3.8). This energy is achieved from implementing the TOU program with consumers \( \{c = 1, 2, \ldots, N_c\} \) over the given horizon \( T \).

\[
E(TOU) = \sum_{c=1}^{N_c} \sum_{t=1}^{T} D_0(c, t) \cdot \sum_{p=1}^{N_p} E(c, t, p) \cdot \left( \frac{\lambda(c, p) - \lambda_0(c, p)}{\lambda_0(c, p)} \right) d(t) \tag{3.8}
\]

Based on the difference between \( \lambda_0(c, p) \) (the initial price dedicated to consumer \( c \) in period \( p \)) and \( \lambda(c, p) \) (the TOU price offered to consumer \( c \) in period \( p \)) as well as depending on the elasticity of consumer \( c \) during time \( t \) with regards to the electricity price in period \( p \) \( (E(c, t, p)) \), the amount of energy obtained from the TOU program is calculated.

3.4.2 Reward-Based DR

The reward-based DR is proposed in a stepwise function as shown in Figure 3.4.

![Figure 3.4. Reward-based DR curve](image)

According to Figure 3.4, the amount of load reduction grows in a stepwise manner as the aggregator offers higher rewards. This function is expressed in the following equations:

\[
P^{DR}(t) = \sum_{w \in \Omega_w} \pi(w) \cdot \sum_{j=1}^{N_j} P_F(w, t) \cdot R_j^{DR}(t) \cdot v_{DR,j}(t) \tag{3.9}
\]
Chapter 3. A New Demand Response Framework

\[ R_{j=1}^{DR}(t) \leq v_{DR,j}(t) \leq R_{j}^{DR}(t) \leq \bar{R}_{j}^{DR}(t) \cdot v_{DR,j}(t) \]  
\[
R^{DR}(t) = \sum_{j=1}^{N_{j}} R_{j}^{DR}(t)
\]  
\[
\sum_{j=1}^{N_{j}} v_{DR,j}(t) = 1
\]

Equation (3.9) indicates the DR volume \((P^{DR}(t))\) obtained from the reward-based DR program. \(v_{DR,j}(t)\) is a binary variable showing the level of the reduced load in the DR curve. This variable is determined according to the reward offered by the DR aggregator. That is, if the offered reward is within the \(j\)th level of the reward boundary (Equation (3.10)), this level is chosen and consequently \(v_{DR,j}(t)\) is equal to one. \(PF(w,t)\) is a scenario-based participation factor which models the uncertainty of customers’ behaviour. This factor ranges between 0 and 1, where zero means no reward-based DR is attainable and \(PF(w,t) = 1\) indicates that the anticipated DR is accessible. Finally, \(\pi(w)\) is the probability of scenario \(w\).

Note that the reward offered to consumers \((R^{DR}(t))\) is calculated as the total rewards of all steps lower than or equal to the \(j\)th level (Equation (3.11)). Constraint (3.12) ensures that only one level of the stepwise reward-based DR can be selected.

The cost of the reward-based DR is given in (3.13):

\[ EC(RDR) = \sum_{w \in \Omega_{w}} \pi(w) \cdot T \cdot \sum_{i=1}^{N_{j}} \sum_{j=1}^{N_{j}} PF(w,t) \cdot R^{DR}_{j}(t) \cdot \bar{R}^{DR}_{j}(t) \cdot d(t) \]  

3.4.3 Overall Problem

The overall problem is formulated as a profit function represented by (3.14). It consists of the revenue of selling DR through fixed DR contracts and DR option agreements, as well as the cost of the reward-based DR. The last component is Conditional Value-at-Risk (CVaR), which is weighted using the risk factor \((\rho)\). \(\xi\) and \(\eta_{w}\) are auxiliary variables for calculating CVaR [56]. \(\beta\) is the confidence level, which usually equals 0.95. Note that the risk level \((\rho = [0-\infty])\) represents the trade-off between the expected profit and the risk. A conservative aggregator willing to minimize the risk chooses a large value of the risk level. On the other hand, a risk-taker aggregator prefers higher profits and consequently selects a risk factor close to 0. Note that risk-factor throughout the thesis is indicated using \(\rho\) (Rho).
Chapter 3. A New Demand Response Framework

\[
\text{Max } \sum_{t=1}^{T} \left[ \left( \sum_{f=1}^{N_{FDR}} \sum_{b=1}^{N_{BDR}} P_{f,b}^D(t) \lambda_{f,b}^D(t) d(t) \right) + \left( \sum_{o=1}^{N_o} \left[ P_o(t) \lambda_o(t) v_o(t) d(t) - (1 - v_o(t)) f_o^{pen}(t) \right] \right) \right]
\]

\[
- \sum_{w \in \Omega_w} \pi(w) \sum_{t=1}^{T} \left( \sum_{j=1}^{N_j} PF(w,t) f_j^{DR}(t) R_j^{DR}(t) d(t) \right) + \rho(z) - \frac{1}{1 - \beta} \sum_{w \in \Omega_w} \eta(w) \pi(w)
\]

(3.14)

It should be noted that it is assumed consumers have smart meters and therefore the cost of installing meters is not included in the profit function.

The profit function is subject to the following constraints:

1- CVaR constraints

\[
\sum_{t=1}^{T} \left( \sum_{o=1}^{N_o} \left[ P_o(t) \lambda_o(t) v_o(t) d(t) - (1 - v_o(t)) f_o^{pen}(t) \right] \right) + \xi - \eta(w) \leq 0; \forall w
\]

(3.15)

\[
\eta(w) \geq 0; \forall w
\]

(3.16)

2- Power balance equation (3.17):

\[
P_o(t) v_o(t) d(t) + \sum_{f=1}^{N_{FDR}} \sum_{b=1}^{N_{BDR}} P_{f,b}^D(t) d(t) = P_{DR}^D(t) d(t) - \sum_{c=1}^{N_c} D_0(c,t) \sum_{p=1}^{N_p} E(c,t,p) \left( \frac{\lambda(c,p) - \lambda_0(c,p)}{\lambda_0(c,p)} \right)
\]

(3.17)
3- Reward-based DR constraints (3.18)-(3.21);

\[
P^{DR}(t) = \sum_{w \in \Omega_w} \pi(w) \sum_{j=1}^{N_j} P^F(w,t) \bar{R}^{DR}_j(t) \nu_{DR,j}(t)
\]

(3.18)

\[
R^{DR}(t) = \sum_{j=1}^{N_j} R^{DR}_j(t)
\]

(3.19)

\[
\bar{R}^{DR}_{j-1}(t) \leq R^{DR}_j(t) \leq \bar{R}^{DR}_j(t) \nu_{DR,j}(t)
\]

(3.20)

\[
\sum_{j=1}^{N_j} \nu_{DR,j}(t) = 1
\]

(3.21)

4- Fixed DR contract size limitation (3.22)

\[
P^{DR,MIN}_{f,b}(t) \leq P^{DR}_{f,b}(t) \leq P^{DR,MAX}_{f,b}(t)
\]

(3.22)

3.4.4 Case Study

A) Data

The highest consumption day of Queensland in 2013 occurred in summer (January 9th). The load curve of this day is shown in Figure 3.5.

![Load curve of Queensland on 9 January 2013](image)

**Figure 3.5. Load curve of Queensland on 9 January 2013 [128]**

A working day in summer is also considered in this study, which is divided into two periods, peak and off-peak. Peak time is between 9am and 10pm, while other times are considered as off-
peak periods. It is assumed that the aggregator buys DR from consumers to sell it to purchasers during peak time, while this flow is reversed during off peak periods. Industrial, commercial and residential consumers are considered here. TOU prices for each consumer are derived from retail tariffs in Queensland, Australia [130] (Table 3.1). The elasticity matrix is also provided in Table 3.2 [18].

### Table 3.1. Retail price tariffs in Queensland

<table>
<thead>
<tr>
<th></th>
<th>Non TOU</th>
<th>TOU</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Normal</td>
<td>Peak</td>
</tr>
<tr>
<td>Residential</td>
<td>29.4</td>
<td>34.6</td>
</tr>
<tr>
<td>Commercial</td>
<td>33.1</td>
<td>42.4</td>
</tr>
<tr>
<td>Industrial</td>
<td>25.5</td>
<td>28.1</td>
</tr>
</tbody>
</table>

### Table 3.2. Elasticity matrix

<table>
<thead>
<tr>
<th></th>
<th>Peak</th>
<th>Off Peak</th>
</tr>
</thead>
<tbody>
<tr>
<td>Residential Peak</td>
<td>-0.15</td>
<td>0.05</td>
</tr>
<tr>
<td>Residential Off Peak</td>
<td>0.02</td>
<td>-0.03</td>
</tr>
<tr>
<td>Commercial Peak</td>
<td>-0.16</td>
<td>0.06</td>
</tr>
<tr>
<td>Commercial Off Peak</td>
<td>0.03</td>
<td>-0.04</td>
</tr>
<tr>
<td>Industrial Peak</td>
<td>-0.2</td>
<td>0.1</td>
</tr>
<tr>
<td>Industrial Off Peak</td>
<td>0.07</td>
<td>-0.08</td>
</tr>
</tbody>
</table>

Unique reward-based DR curves involving 25 steps are assumed for each sector. A typical reward-based curve used in the peak period is shown in Figure 3.6. Furthermore, a scenario-based participation factor is created as follows. For each reward-based DR, 20 scenarios representing consumer uncertainties are randomly generated. These scenarios range between zero and one. Zero means no DR participation by consumers. However, higher values of scenarios correspond to higher participation, where participation factor equal to one indicates the entire anticipated DR is attainable.
A fixed DR contract involving six blocks is considered for each period. The maximum demand of each block is 90kW and 30kW during peak and off-peak periods, respectively. In addition, the price for each fixed DR block is given in Table 3.3.

<table>
<thead>
<tr>
<th>Fixed DR 1</th>
<th>Block 1</th>
<th>Block 2</th>
<th>Block 3</th>
<th>Block 4</th>
<th>Block 5</th>
<th>Block 6</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>36</td>
<td>37</td>
<td>38</td>
<td>39</td>
<td>40</td>
<td>41</td>
</tr>
<tr>
<td>Fixed DR 2</td>
<td>15</td>
<td>16</td>
<td>18</td>
<td>20</td>
<td>21</td>
<td>23</td>
</tr>
</tbody>
</table>

Four DR option agreements are modelled for each period. The prices and demand volumes for each agreement are provided in Table 3.4. Note that the penalty of not exercising each DR option is assumed to be 10% of the contract’s value.

<table>
<thead>
<tr>
<th>Demand (MW)</th>
<th>Price ($/MWh)</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Peak</td>
<td>Off Peak</td>
<td>Peak</td>
<td>Off Peak</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DR Option 1</td>
<td>50</td>
<td>-50</td>
<td>34</td>
<td>21</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DR Option 2</td>
<td>50</td>
<td>-50</td>
<td>37</td>
<td>20</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DR Option 3</td>
<td>50</td>
<td>-30</td>
<td>36</td>
<td>22</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DR Option 4</td>
<td>50</td>
<td>-25</td>
<td>35</td>
<td>18</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

B) Simulation Results

The problem is formulated in a mixed-integer linear programming approach and is solved for different risk levels using CPLEX 11.1.1 under GAMS [131]. Figure 3.7 depicts the TOU outcome. It can be seen that consumers reduce their consumption during peak periods, while they use more energy during off-peak time. The reduction during peak time is approximately 7% and the load growth in off-peak periods is 5.54%. Note that the outcome of the TOU only depends on consumers’ elasticity, and it is constant for various risk levels.
Figure 3.7. TOU results

Figure 3.8 illustrates the reward-based DR achievements. During the peak period, the risk-neutral DR aggregator (risk factor equal to 0) has a higher level of involvement in this program, i.e. it obtains around 2,700 kWh DR from consumers. However, increasing the risk level leads to a declining trend in this program. This is reasonable since this program involves uncertainty and hence conservative aggregators prefer to reduce their share from it. This trend is also valid for the off-peak period. It should be noted that negative values during off-peak periods mean that the aggregator sells the reward-based DR to consumers. In other words, consumers are encouraged to consume more energy through this program during off peak. It can be seen that while the risk-neutral DR aggregator encourages consumers to use just under 1,500 kWh more energy, the share of the most risk-averse aggregator (risk factor equal to 2) decreases to just above 1,000 kWh.

Figure 3.8. Reward-Based DR results
Table 3.5 shows the energy traded in fixed DR contracts. The aggregator sells DR to purchasers in the peak period, while it buys energy during off-peak time. It can also be said that the risk-averse aggregator ($\rho = 2$) trades more fixed DR than the risk-neutral one ($\rho = 0$) in both periods. This is because fixed DR contracts involve no risk and thus, risk-averse aggregators prefer to increase their DR share from them.

<table>
<thead>
<tr>
<th>$\rho$</th>
<th>Peak</th>
<th>Off Peak</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>4559</td>
<td>-1004</td>
</tr>
<tr>
<td>1</td>
<td>4539</td>
<td>-1004</td>
</tr>
<tr>
<td>2</td>
<td>4735</td>
<td>-1074</td>
</tr>
</tbody>
</table>

Table 3.6 represents the exercised DR options for different risk levels. All DR options are used for risk factors 0 and 1. For $\rho = 2$, DR options (DROP) 1 and 3 are not exercised during peak and off-peak periods, respectively. This trend follows the declining tendency of the reward-based DR as a result of increasing the risk level.

<table>
<thead>
<tr>
<th>$\rho$</th>
<th>Peak</th>
<th>Off Peak</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>All</td>
<td>All</td>
</tr>
<tr>
<td>1</td>
<td>All</td>
<td>All</td>
</tr>
<tr>
<td>2</td>
<td>DROP2-DROP4</td>
<td>DROP1, DROP2, DROP4</td>
</tr>
</tbody>
</table>

Finally, the impact of the unpredictable behaviour of consumers is evaluated here. Two cases are considered: Case 1 represents the outcome when the uncertainty is modelled (for the risk-neutral aggregators) and case 2 ignores the unpredictable behaviour of customers ($PF(w, t) = 1$ in the reward-based DR). The amounts of TOU and DR options remain constant in both cases. But the reward-based DR and fixed DR contracts change as Figure 3.9. As can be seen, disregarding the customers’ behaviour results in a higher reward-based DR outcome and consequently, higher amounts of fixed DR. That is, the DR aggregator which assumes all customers will definitely participate in the reward-based DR may achieve less DR in practice. This shows how ignoring customers’ behaviour may mislead the aggregator in its energy plan.
3.5 Summary

This chapter presents the proposed DR framework. To this end, DR is considered as a public good, which is traded between DR purchasers and DR aggregators. Various DR contracts are proposed for this purpose. Each contract is described and formulated accordingly. In addition, a case study from a DR aggregator’s point of view is provided and the results are analysed to show the validity of the proposed DR framework.

The proposed DR framework will be employed in the following chapters and its applications for electricity markets are evaluated. In particular, the proposed DR contracts are assessed for wind power producers (Chapters 4-6) and electricity retailers (Chapter 7) as two market players on the supply and demand sides. In addition, a DR aggregator is considered to be able to participate in the reserve market, where its validity is examined in a market analysis from an ISO’s point of view (Chapter 8).

3.6 Nomenclature

A) Indices

\( b \) \quad \text{Index for blocks of fixed DR} \quad (b = 1, \ldots, N_{BDR})

\( c \) \quad \text{Index for customers} \quad (c = 1, \ldots, N_c)

\( f \) \quad \text{Index for fixed DR} \quad (f = 1, \ldots, N_{FDR})
flex \quad \text{Index for flexible DR (} flex = 1,...,N_{flex})

j \quad \text{Index for intervals of the reward-based DR (} j = 1,...,N_j)

o \quad \text{Index for DR options (} o = 1,...,N_o)

p \quad \text{Index for time period in the TOU program (} p = 1,...,N_p)

t \quad \text{Index for time (} t = 1,...,T)

w \quad \text{Index for scenarios (} w = 1,...,N_w \in \Omega_w)

\textbf{B) Parameters}

\quad d(t) \quad \text{Duration of time period } t

\quad D_0(c,t) \quad \text{Initial demand of consumer } c \text{ in time } t

\quad E(c,t,p) \quad \text{Elasticity of consumer } c \text{ in time } t \text{ with respect to price at time } p

\quad EP \quad \text{End of period for flexible DR } flex

\quad E^{Agrd}_{flex} \quad \text{Energy agreed in step 1 for the flexible DR } flex

\quad f_o^{pen}(t) \quad \text{Penalty of not exercising DR option } o \text{ in period } t

\quad P^{DR,MAX}_{f,b}(t) \quad \text{Maximum fixed DR } f \text{ in block } b

\quad P^{DR,MIN}_{f,b}(t) \quad \text{Minimum fixed DR } f \text{ in block } b

\quad P^{DR,MAX}_{flex}(t) \quad \text{Maximum flexible DR } flex

\quad P^{DR,MIN}_{flex}(t) \quad \text{Minimum flexible DR } flex

\quad \overline{P}_{f}^{DR}(t) \quad \text{Upper level of the } j \text{ interval of the reward-based DR}

\quad PF(w,t) \quad \text{Scenario-based participation factor}

\quad \overline{R}_{f}^{DR}(t) \quad \text{Reward in the } j \text{ interval of the reward-based DR curve}

\quad SP \quad \text{Start of period for flexible DR } flex

\quad \lambda(c,p) \quad \text{Time of use price}

\quad \lambda^{DR}_{f,b}(t) \quad \text{Price of fixed DR } f \text{ in block } b

\quad \lambda^{DR}_{flex}(t) \quad \text{Price of flexible DR } flex
Chapter 3. A New Demand Response Framework

\[ \lambda_o(t) \]  \quad \text{Price of DR option } o

\[ \lambda_0(c, p) \]  \quad \text{Initial price offered to consumer } c \text{ in period } p

\[ \pi(w) \]  \quad \text{Probability of scenario } w

\[ \rho \]  \quad \text{Risk factor}

C) Variables

\[ E^{\text{Agd}}_{\text{flex}} \]  \quad \text{Energy agreed in the first stage of flexible DR} flex

\[ P_{\text{flex}}^\text{DR}(t) \]  \quad \text{Power of flexible DR} flex

\[ P_{f,b}^\text{DR}(t) \]  \quad \text{Power of fixed DR} f \text{ in block } b

\[ P_o(t) \]  \quad \text{Power of DR option } o

\[ R_j^\text{DR}(t) \]  \quad \text{Reward of the } j \text{th interval of the reward-based DR}

\[ v_{ao}(t) \]  \quad \text{Binary variable for American DR option } ao

\[ v_{\text{DR},j}(t) \]  \quad \text{Binary variable for the reward-based DR function}

\[ v_o(t) \]  \quad \text{Binary variable for DR option } o

\[ \xi, \eta(w) \]  \quad \text{Auxiliary variables for calculating CVaR}

D) Numbers and Sets

\[ N_{ao} \]  \quad \text{Number of American DR options}

\[ N_{BDR} \]  \quad \text{Number of blocks for fixed DR}

\[ N_c \]  \quad \text{Number of consumers}

\[ N_{FDR} \]  \quad \text{Number of fixed DR}

\[ N_{\text{flex}} \]  \quad \text{Number of flexible DR}

\[ N_j \]  \quad \text{Number of intervals in the reward-based DR}

\[ N_o \]  \quad \text{Number of DR options}

\[ N_p \]  \quad \text{Number of periods}

\[ T \]  \quad \text{Set of time periods}

\[ T_{ao} \]  \quad \text{Set of time periods in American DR options}

\[ \Omega_w \]  \quad \text{Set of scenarios}
Chapter 4

Employing Demand Response by Wind Power Producers

4.1. Introduction

Wind power is a leading renewable energy resource. Various incentive schemes and policies are provided to facilitate the application of wind energy worldwide. The European Union has a target of achieving 20% of renewable energy by 2020. The Renewable Energy Target (RET) in Australia sets the same requirement by 2020. Different states in the U.S have distinct goals. For instance, California is planning to obtain 33% of its energy from renewable technologies by 2020 [101].

It is expected that wind power producers could be treated similar to conventional generators in the near future. This is currently the case for some wind power producers in Germany [101], Western Denmark [12] and Australia, while it is voluntary in other markets such as the Spanish [14] and Midwest ISO (MISO) markets [101]. Therefore, wind power producers place their offer in the market while they are responsible for their production deviation in real time. Two main practical solutions for this issue are presented in literature: Optimal trading strategies and a joint operation of wind power producers and easily controllable resources.

Optimal trading strategies are addressed in some investigations such as [55, 56, 61], where they mostly work on the imbalance cost minimization concept. In addition, joint operation strategies are

---

1 This chapter covers the following references:

For the Australian National Electricity Market (Section 4.3):

For the Nordic Market (Section 4.4):
addressed in [13-15, 67], where the coordination of wind power producers and other resources such as storage and hydro units is assessed. Demand response (DR) is another source, which can be used in a joint operation with wind power producers. Relevant studies in literature mostly investigate this to improve network and market operations [74, 75, 112, 115]. A few papers investigate DR applicability from wind power producers’ point of view. For instance, the authors in [76] propose a method in which a virtual power plant is modelled to coordinate wind power and demand response. In addition, the authors in [132] investigate smart grid roles in activating passive loads to mitigate wind power variations.

This chapter aims at using DR in offering strategies by wind power producers in two well-known electricity markets with unique features, i.e. the Australian National Electricity Market (NEM) [3, 128] and the Nordic market [133, 134]. A proper offering plan is proposed for each market, through which a wind power producer is able to employ DR from a DR aggregator. For this purpose, the proposed DR framework and DR contracts presented in Chapter 3 are used here.

The chapter is structured as follows. First, the structures of the Australian National Electricity Market (NEM) and the Nordic market are addressed. Then, the proposed wind offering strategy for the Australian National Electricity Market (NEM) is formulated and studied. Finally, this strategy is modified for the Nordic market and evaluated based on its structure. Note that all indices, constants and variables throughout the chapter are explained in Section 4.6.

4.2. The Australian National Electricity Market vs. the Nordic market

A trading day in the Australian NEM begins at 4:00am and ends at 4:00am of the next day. Each trading period represents a half hourly period, which comprises six 5-minute dispatch intervals. According to the NEM, generators place their offers at 12:30pm on the day before the energy delivery. Then, they are allowed to rebid their energy volume up until five minutes prior to the dispatch.

The Nordic market comprises a day-ahead market, an adjustment (intraday) market and a balancing (regulating) market [55]. The day-ahead market closes at 12:00pm the preceding day. Additionally, the market involves an adjustment market, called Elbas. This market opens at 15:00 on the same day and lasts up until one hour prior to the delivery. Finally, the market operator guarantees real-time balances through the regulating market which takes place just before the energy delivery.

Accordingly, while the Australian NEM takes preliminary action on the day prior to energy delivery and then implements correction actions just before the energy delivery, the Nordic market has two settlements, i.e. day-ahead and balancing market floors, where energy can be traded in them.
4.3. Wind Offering Strategy in the Australian National Electricity Market

4.3.1. The Proposed Two-Step Plan

The proposed offering plan is expressed in two steps as shown in Figure 4.1. This plan is adjusted to the Australian NEM, where the pre-dispatch process closes at 12:30 pm on the day prior to the energy delivery (Step 1) and then, generators are able to change the volume of their offer up until 5 minutes before the dispatch (Step 2). Note that Ancillary services markets are not modelled here. Therefore, the offering strategy in the Australian NEM consists of a preliminary action which takes place on the preceding day and a corrective one which can be made up to 5 minutes before the real-time dispatch.

Preliminary decisions are taken in step 1. For this purpose, a stochastic programming approach is formulated through which initial energy offers are decided. In addition, the wind power producer negotiates the required DR agreements with a DR aggregator. Three DR contracts are considered here: DR options, fixed DR contracts and flexible DR agreements. These decisions are made while both market prices and wind power production are uncertain. To model the risk associated with this uncertainty, conditional Value-at-risk (CVaR) is used.

The second step covers the decisions taken at the real-time dispatch. A successive approach is applied, which runs for each dispatch interval until all intervals are covered. The volume of energy to be offered for each interval is determined. In addition, the wind power producer approves its final DR agreements for the relevant interval. Similar to step 1, a stochastic programming problem is formulated for this step in which power production and the market price are known for the current interval, but they are still uncertain in the remaining intervals. In addition, CVaR is used to assess the risk.

It is assumed that the wind power producer is the price-taker. A further assumption is that the wind power producer is treated as similar to conventional power plants, i.e. scheduled generators in the NEM, where it is responsible for its bidding strategy and production variations. In addition, this work assumes a single-node market in which the transmission network is not modelled. This is a common practice in bidding strategy problems investigated in literature [55, 56]. Finally note that this study considers DR trading in both directions, i.e. from the DR aggregator to the wind power producer and in the opposite direction. Indeed, in the case of a power shortage, the wind power producer is a DR buyer while during excess production the producer sells energy to the DR aggregator.
4.3.1.1. Step 1: Initial Offering

This step takes place at 12:30 pm the preceding day. The wind power producer runs a preliminary strategy. The producer achieves an initial offering schedule over all periods of the next day \((t = \{1, 2, ..., FI\})\). In addition, fixed DR contracts are negotiated. Furthermore, the wind power producer determines the periods in which DR options are signed. Finally, flexible DR agreements are set. These decisions are taken under the uncertainty of spot prices and wind power production, where these parameters are stochastically modelled through a set of scenarios to represent their plausible realizations.

A stochastic profit function is formulated in this step, which consists of the following terms.

1. The expected revenue obtained from selling energy to the spot market:

\[
ER^{SM} = \sum_{w=1}^{N_w} \pi (w). \sum_{t=1}^{FI} P^{s,s1}(t,w) \lambda^{s,s1}(t,w) d(t) \tag{4.1}
\]

2. The cost of the DR option modelled in step 1: This step determines whether a DR option is signed or not. This decision is indicated by a binary variable, i.e. \(Sgn_o(t)\). Zero specifies that the wind power producer does not sign the contract, while 1 means the contract is set in this step.

\[
C^{DRO,S1}_o(t) = P_o(t). \lambda_o(t). Sgn_o(t) d(t) \quad \forall o = 1, 2, ..., N_o \tag{4.2}
\]

3. The cost of block \(b\) of fixed DR \(f\), as given in (4.3); Expression (4.4) shows the margin size of each contract’s block.
Chapter 4. Employing Demand Response by Wind Power Producers

\[ C_{f,b}^{DR}(t) = p_{f,b}^{DR}(t) \lambda_{f,b}^{DR}(t) \cdot d(t) \quad \forall f = 1, \ldots, N_{FDR}, \forall b = 1, \ldots, N_{BDR} \]  
\[ (4.3) \]

\[ P_{f,b}^{DR.MIN}(t) \leq p_{f,b}^{DR}(t) \leq P_{f,b}^{DR.MAX}(t) \]  
\[ (4.4) \]

4. The cost of a flexible DR agreement in step 1, as formulated in (4.5); the size of each flexible DR is imposed by (4.6).

\[ C_{flex}^{DR,S1}(t) = p_{flex}^{DR,s1}(t) \lambda_{flex}^{DR}(t) \cdot d(t) \quad \forall flex = 1, \ldots, N_{flex} \]  
\[ (4.5) \]

\[ P_{flex}^{DR.MIN}(t) \leq p_{flex}^{DR,s1}(t) \leq P_{flex}^{DR.MAX}(t) \quad \forall flex = 1, \ldots, N_{flex} \]  
\[ (4.6) \]

5. The last component is CVaR [56] which is weighted using the risk factor (\( \rho \)). Note that the risk level (\( \rho = [0-\infty) \)) represents the trade-off between the expected profit and the risk. A risk-averse wind power producer willing to minimize the risk chooses a large value of the risk factor. On the other hand, a risk-neutral producer prefers higher profits and consequently selects a risk factor close to 0.

The overall profit function (PF) of step 1 is given in (4.7). Constraints (4.8) and (4.9) impose the size limits of power traded in the fixed DR and flexible DR agreements, respectively. Expressions (4.10) and (4.11) represent CVaR constraints. These constraints are used to linearize CVaR [56]. Finally, the power balance is satisfied in (4.12), where the offered power to the market must be equal to the wind power production (\( P^{w,s1}(t, w) \)) plus the power procured from DR. Indeed, this constraint ensures that the decisions on the initial wind power offer and DR agreements are valid for each power production scenario.

\[ \text{Maximize } PF = ER^{SM} - \sum_{t=1}^{FI} \sum_{o=1}^{N_o} C_{o}^{DRO,S1}(t) - \sum_{t=1}^{FI} \sum_{f=1}^{N_{FDR}} \sum_{b=1}^{N_{BDR}} C_{f,b}^{FDR}(t) \]

\[ - \sum_{t=1}^{FI} \sum_{flex=1}^{N_{flex}} C_{flex}^{DR,S1}(t) + \rho \left( \xi - \frac{1}{1-\beta} \sum_{w=1}^{N_w} \eta(w) \pi(w) \right) \]  
\[ (4.7) \]

subject to,

\[ P_{f,b}^{DR.MIN}(t) \leq p_{f,b}^{DR}(t) \leq P_{f,b}^{DR.MAX}(t) \]  
\[ (4.8) \]

\[ P_{flex}^{DR.MIN}(t) \leq p_{flex}^{DR,s1}(t) \leq P_{flex}^{DR.MAX}(t) \]  
\[ (4.9) \]
Employing Demand Response by Wind Power Producers

\[
\begin{align*}
\sum_{t=1}^{FI} P^{s,s1}(t,w) \lambda^{s,s1}(t,w) . d(t) + \sum_{t=1}^{FI} \sum_{o=1}^{N_o} C^DRO, S1(t) \\
+ \sum_{t=1}^{FI} N_{EDR} N_{BDR} \sum_{f=1}^{N_{EDR}} \sum_{b=1}^{N_{BDR}} C^{FDR}(t) + \sum_{t=1}^{FI} \sum_{b=1}^{N_{EDR}} \sum_{o=1}^{N_{BDR}} C^{EDR}(t, w) \\
+ \xi - \eta(w) \leq 0 \quad \forall w = 1, 2, ..., N_w \\
\eta(w) \geq 0; \quad \forall w = 1, 2, ..., N_w
\end{align*}
\]

(4.10)

\[
P^{s,s1}(t,w) = P^{w,s1}(t,w) + \sum_{f=1}^{N_{EDR}} \sum_{b=1}^{N_{BDR}} P^{FDR}(t) \\
+ \sum_{o=1}^{N_o} P_o(t) . Sgn_o(t) + \sum_{f=1}^{N_{EDR}} \sum_{b=1}^{N_{BDR}} P^{EDR, S1}(t) \quad \forall w = 1, 2, ..., N_w, \forall t = 1, ..., FI
\]

(4.11)

4.3.1.2. Step 2: Optimal Offering

Step 2 deals with the actions required to modify the decisions made in the previous step (See Figure 4.1). It begins at 4:00am and runs for each 5-minute dispatch interval. This step employs a successive algorithm which iterates from interval 1 until the last interval. For each interval, the following decisions are made. 1) The optimal offering energy for the current interval is determined. 2) It is decided whether the signed DR options in step 1 are exercised for that interval. 3) The required volume of flexible DR for the relevant interval is decided.

A new profit function is formulated which is solved for each iteration. This function is given in (4.13).

Maximize \( PF = \text{Prof}(t) \bigg|_{t=CI} + \text{EProf}(t) \bigg|_{t=CI+1} + \rho \cdot \text{CVaR} \) (4.13)

where,

\[
\text{Prof}(t) \bigg|_{t=CI} = \sum_{s=1}^{Ns} \pi(s) \cdot \sum_{t=CI+1}^{FI} P^{s,s2}(t,s) \cdot \lambda^{s,s2}(t,s) . d(t) - \sum_{o=1}^{N_o} C^DRO, S2(CI) - \sum_{flex=1}^{N_{Flex}} C^{FlexDR, S2}(CI)
\]

(4.14)

\[
\text{EProf}(t) \bigg|_{t=CI+1} = \sum_{s=1}^{Ns} \sum_{t=CI+1}^{FI} P^{s,s2}(t,s) \cdot \lambda^{s,s2}(t,s) . d(t) \\
- \sum_{t=CI+1}^{FI} \sum_{o=1}^{N_o} C^DRO, S2(t) - \sum_{flex=1}^{N_{Flex}} C^{FlexDR, S2}(t)
\]

(4.15)

\[
\text{CVaR} = \xi - \frac{1}{1 - \beta} \sum_{s=1}^{Ns} \eta(s) \pi(s)
\]

(4.16)
subject to,

\[ P_{\text{flex}}^{\text{DR,MIN}}(t) \leq P_{\text{flex}}^{\text{DR,s1}}(t) \leq P_{\text{flex}}^{\text{DR,MAX}}(t) \quad (4.17) \]

\[ EP \sum_{t=SP} P_{\text{flex}}^{\text{DR,s1}}(t) d(t) = E_{\text{flex}}^{\text{Agrd,s1}} \forall \text{flex} = 1,\ldots,N_{\text{flex}} \quad (4.18) \]

\[ - \sum_{t=1}^{FI} P_{t}^{\text{w,s1}}(t) \alpha_{s,t}^{s1} - \sum_{t=1}^{FI} \sum_{o=1}^{N_{\text{o}}^{\text{BDR}}} C_{o}^{DRO,s1}(t) \]

\[ + \sum_{t=1}^{FI} \sum_{s=1}^{N_{\text{flex}}} C_{s}^{\text{flex}} D R, s 1 (t) \]

\[ - \sum_{t=1}^{FI} \sum_{s=1}^{N_{\text{flex}}} C_{s}^{\text{flex}} D R, s 1 (t) + \xi - \eta(s) \leq 0 \quad \forall s = 1,\ldots,N_{s} \quad (4.19) \]

\[ \eta(s) \geq 0; \quad \forall s = 1,\ldots,N_{s} \quad (4.20) \]

\[ P_{t}^{\text{w,s1}}(t) = P_{t}^{\text{w,s}}(t) + \sum_{f=1}^{N_{\text{fDR}}} \sum_{b=1}^{N_{\text{bDR}}} P_{f,b}^{\text{DR}}(t) \]

\[ + \sum_{o=1}^{N_{o}} P_{o}(t) S g n_{o}(t) \nu_{o}(t) + \sum_{s=1}^{N_{\text{flex}}} P_{s}^{\text{DR,s1}}(t) \quad (4.21) \]

The profit function comprises three main terms:

1. The profit obtained in the current interval \((t = CI)\). This function is shown in (4.14), where it involves the revenue obtained from selling energy into the spot market minus the cost of DR options and flexible DR. Note that since the current interval is very close to the real time dispatch, the spot price and wind power production are assumed to be deterministic parameters here. Thus the obtained profit for the current interval is not associated with uncertainty.

2. The expected profit over the following periods until the final interval \((t = CI + 1 \rightarrow FI)\): Equation (4.15) provides this function. Since price and wind forecasts for the following intervals involve a level of uncertainty, these parameters are illustrated using corresponding scenarios. Note that scenarios in step 2 are represented by index \(s\).

3. The CVaR risk measure which is shown in (4.16).

Note that the costs of DR contracts in step 2 are determined as follows.

1. The cost of DR option in step 2: This step is valid for those DR options signed in the previous step, i.e. \(S g n_{o}(t) = 1\). Indeed, step 2 decides the exercising status of these signed contracts. A binary variable \(\nu_{o}(t)\) is used, which is equal to 1 if the contract is exercised and zero if not.
The cost of flexible DR in step 2: A cost function similar to step 1 is defined for step 2. However, an additional constraint is required in step 2, as represented in (4.23). Indeed this constraint enforces that the overall volume of each flexible DR used in step 2 must be equal to its volume contracted in step 1, i.e. $E_{flex}^{Agrd,s1}$. Note that $SP$ and $EP$ represent the start and end of the period that flexible DR is valid.

$$\sum_{t=SP}^{EP} P_{flex}^{DRO,s2}(t) = E_{flex}^{Agrd,s1}$$  \hspace{1cm} (4.23)

Note that the fixed DR volume determined in the previous step is used in step 2 without any changes. Thus the term indicating the fixed DR cost is not included in the profit function of this step.

The profit function is subject to constraints (4.17)-(4.21). Constraint (4.17) enforces the size limitation of each flexible DR. In addition, equation (4.18) indicates that the total energy volume of each flexible DR must be equal to the contracted volume ($E_{flex}^{Agrd,s1}$) obtained in step 1. Expressions (4.19) and (4.20) show CVaR constraints. Finally, equation (4.21) imposes the power balance. Note that in this constraint, wind power production ($P_{wind,s2}(s,t)$) is known for the current interval. However, it is uncertain in the following intervals. In addition, it is important to emphasize the necessity of including the fixed DR volume in the power balance constraint of step 2.

### 4.3.2. Case Study

#### 4.3.2.1. Data Preparation and Assumptions

The proposed offering plan is evaluated on a realistic case of the South Australian (SA) jurisdiction within the Australian NEM. The available spot price and wind speed are in half-hourly resolutions. Hence, it is assumed that each given interval in this study is 30 minutes [128].

The spot price and wind power production are uncertain parameters and thus they are characterized using proper scenarios. Similar to relevant studies [56], ARIMA models are chosen for generating price scenarios. A time series of the spot prices of SA from December 2011 to January 2012 is used to generate price scenarios [128]. As a result, 40 price scenarios are generated for step 1.

The wind power producer Lake Bonney 2 is chosen [135]. This producer is located at Mt Gambier AERO and its installed capacity is 159MW (53 Vestas 3MW Turbines). In order to provide wind power scenarios, first, wind speed scenarios are generated using the ARMA model.
Summer season data from 2007-2012 is used as the input time series. Twenty wind speed scenarios are generated for step 1. These scenarios are then transformed to power scenarios using the Vestas Wind curve [136].

Note that the adequate number of scenarios is mainly determined using one of the following methods.

1) The first method uses scenario reduction techniques [56]. In this way, the original number of scenarios is reduced in such a way that makes the problem tractable while keeping it accurate. Fast-forward scenario reduction is the most popular method.

2) The second method follows the same aim, but it targets the objective function. That is, the number of scenarios is increased until the expected profit is stabilized [18].

This study uses the second approach, where altogether 800 scenarios are generated. Figure 4.2 verifies this number by illustrating the expected profit versus the number of scenarios for the risk-neutral and risk-averse wind power producers.

Figure 4.2. Expected profit for various number of scenarios

Figure 4.3 displays the expected values of wind power and spot price scenarios in step 1. It can be seen that while the wind power production peak occurs in early intervals, the spot price curve sees its peak in the afternoon.
For step 2, the given price and wind scenarios of step 1 are reduced to 20 and 10, respectively. For this purpose, those scenarios of step 1 which have a higher level of deviation from the average values shown in Figure 4.3 are removed. This is reasonable since step 2 is closer to the trading intervals and hence its uncertainty is lower than that of step 1.

The information of DR contracts is provided in Table 4.1. Since DR contracts data is not available, they are assumed here. In order to reasonably model these contracts, two main concepts are taken into account: first, the prices considered for DR contracts are chosen in a way that they are close to the expected price scenarios shown in Figure 4.3. Secondly, the DR contracts are assigned in such a way that when the wind power producer is in its high production periods and market prices are low, it most likely sells a part of its energy through DR contracts. On the contrary, when the market price is high or there is wind power shortage, the wind power producer is assumed to be mostly a DR buyer in order to compensate its deviations during this time.

Twelve fixed DR contracts are considered. The first three contracts cover the time intervals between 3 and 18. According to the above description, the wind power producer sells energy to the aggregator in these periods. The other contracts consider the remaining intervals where the wind power producer buys fixed DR from the DR aggregator. Six flexible DR agreements are modelled. The wind producer is able to sell/buy up to 20 MW flexible DR in each interval. Finally, four DR options are taken into account, where the penalty of not exercising each option is assumed to be equal to 15% of the contract cost. It is assumed that the wind power producer can sell energy through DR options in the first 18 intervals while it is a DR option buyer during the remaining periods.
Table 4.1. DR contracts details

<table>
<thead>
<tr>
<th>Intervals</th>
<th>Fixed DR</th>
<th>Flexible DR</th>
<th>DR options</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price ranges ($/MWh)</td>
<td>3-48</td>
<td>1-48</td>
<td>1-48</td>
</tr>
<tr>
<td>24-44</td>
<td>20-40</td>
<td>30-44</td>
<td></td>
</tr>
<tr>
<td>Volume ranges (MW)</td>
<td>Sell up to 12</td>
<td>Sell up to 20</td>
<td>Sell up to 10</td>
</tr>
<tr>
<td>Buy up to 15</td>
<td>Buy up to 20</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

4.3.2.2. Numerical Results

A) Decisions in step 1 (S1)

The given problem is mixed-integer linear programming, which is solved using CPLEX 11.1.1 under GAMS [131].

Figure 4.4 displays the expected profit versus the standard deviation for various risk levels. The risk-neutral wind power producer obtains around $23,000 while its profit deviation is just under $15,000. Increasing the risk level leads to a decrement in both values, where for the most risk-averse producer the expected profit and the standard deviation decrease to around $21,000 and $10,000, respectively. In other words, the risk-neutral wind power producer obtains an almost 10% higher profit than the risk-averse producer with the cost of around 45% higher profit deviation.

![Figure 4.4. The expected profit vs. standard deviation](image)

Table 4.2 shows the contracted fixed DR agreements for different levels of risk. A risk-neutral wind power producer ($\rho = 0$) sets 8 fixed DR contracts out of 12 existing ones. This number declines as the producer becomes more risk averse, where for $\rho = 5$, only 3 contracts are employed. This trend is reasonable as risk-averse producers avoid increasing their risk by purchasing energy from resources such as fixed DR and selling it to the spot market.

Table 4.3 represents the intervals in which DR options (DRO) are contracted in step 1. All four DROs are signed for different risk levels. However, the number of signed DR options is reduced as...
the risk level increases. Indeed, the declining trend follows a similar rule to the fixed DR pattern, discussed earlier. In addition, it can be seen that risk-averse producers are generally DR option sellers. They mostly sign DR options during intervals 1-18, where DR options are sold to the DR aggregator.

The volume of contracted flexible DR agreements is shown in Table 4.4. The risk-neutral wind power producer buys 195MWh flexible DR from the aggregator, where all six given agreements are used. Increasing the risk level causes a lower share of flexible DR. This is obvious in $\rho=0.5$ and $\rho=1$, where only the first three contracts are employed and the share of flexible DR decreases to less than half. An interesting result is that the most risk-averse wind power producer ($\rho=5$) sells around 175MWh energy to the DR aggregator. This is sensible since the risk-averse producer prefers to reduce the risk of the market by selling a portion of its energy through the flexible DR agreement.

Table 4.2. Fixed DR contracts

<table>
<thead>
<tr>
<th>$\rho$</th>
<th>Set Contracts</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>FC2,FC4,FC5,FC6,FC7,FC9,FC11,FC12</td>
</tr>
<tr>
<td>0.5</td>
<td>FC2,FC4,FC5,FC6,FC9,FC12</td>
</tr>
<tr>
<td>1</td>
<td>FC2,FC4,FC5,FC6,FC12</td>
</tr>
<tr>
<td>5</td>
<td>FC5,FC6,FC12</td>
</tr>
</tbody>
</table>

Table 4.3. Signed DR options in step 1

<table>
<thead>
<tr>
<th>$\rho$</th>
<th>DRO1</th>
<th>DRO2</th>
<th>DRO3</th>
<th>DRO4</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>8,10-18,31-34,42-44</td>
<td>1-18,29-44,47</td>
<td>15-17,42-44</td>
<td>1,3-9,12,14-15,40-44</td>
</tr>
<tr>
<td>0.5</td>
<td>7,8,10-18,32</td>
<td>1-18,30-34</td>
<td>15-17</td>
<td>1,3-7,12,14,15</td>
</tr>
<tr>
<td>1</td>
<td>7-18</td>
<td>1-18,31-33</td>
<td>15-17</td>
<td>2-5,12,14,15</td>
</tr>
<tr>
<td>5</td>
<td>8,10-18</td>
<td>1,5-16,18,33</td>
<td>4,8,12,14-17</td>
<td>5,7,9</td>
</tr>
</tbody>
</table>

Table 4.4. Contracted flexible DR in step 1(MWh)

<table>
<thead>
<tr>
<th>$\rho$</th>
<th>Flex1</th>
<th>Flex2</th>
<th>Flex3</th>
<th>Flex4</th>
<th>Flex5</th>
<th>Flex6</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>20</td>
<td>50</td>
<td>40</td>
<td>20</td>
<td>25</td>
<td>40</td>
<td>195</td>
</tr>
<tr>
<td>0.5</td>
<td>20</td>
<td>50</td>
<td>2.9</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>72.9</td>
</tr>
<tr>
<td>1</td>
<td>20</td>
<td>50</td>
<td>2.9</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>72.9</td>
</tr>
<tr>
<td>5</td>
<td>-3.6</td>
<td>-11</td>
<td>-50</td>
<td>-20</td>
<td>-25</td>
<td>-65</td>
<td>-174.6</td>
</tr>
</tbody>
</table>

Figure 4.5 shows the initial bids for various risk levels. It can be seen that all wind power producers have lower offers than their expected production in the first 18 intervals, particularly between intervals 5 and 18. That is, they prefer to sell a percentage of their expected power through DR contracts. However, for the rest of the intervals the trend is as follows. Risk taker producers, and ultimately the risk-neutral one ($\rho=0$), have higher offers than their expected production in
intervals after 18. This indicates that they tend to buy DR to resell it to the spot market. However, as the wind power producer becomes more risk averse, this tendency decreases. It can be seen that for these producers the bid is almost equal to or even lower than the wind power expectation. This is correct since risk-averse producers refuse to gain more risk by buying DR and selling it to the spot market as a volatile resource.

![Figure 4.5. The initial offer curves of step 1](image)

**B) Decisions in step 2 (S2)**

This section delivers the results of step 2 for the risk-neutral ($\rho = 0$) and the most risk-averse ($\rho = 5$) wind power producers.

Figure 4.6 compares the initial (step 1) and final (step 2) offer curves for the risk-neutral wind power producer ($\rho = 0$). The initial offer curve is modified in almost all intervals in step 2. In the final offer curve, more power is sold during the first intervals but the share of the following periods decreases. This indeed shows how the risk-neutral producer corrects its initial offers during the real time when more accurate power and spot price expectations are available. It is also obvious that while the final offer is almost the same as the expected wind power in the first 18 intervals, it is higher in the remaining intervals. Indeed, the risk-neutral producer aims to increase its profit though buying DR and selling it to the market in the last intervals.
Chapter 4. Employing Demand Response by Wind Power Producers

Figure 4.6. The initial offer curve (S1) vs. the final offer curve (S2) - $\rho=0$

The distribution of flexible DR agreements employed by the risk-neutral wind power producer in steps 1 and 2 is provided in Figure 4.7. Each sub-figure shows the outcome of one flexible DR agreement. Note that X-axis represents the intervals during which each flexible DR agreement is valid. The wind power producer changes the usage configurations of flexible DR contracts 1, 2, 3 and 6 in step 2. Significant modifications are made in contract 2, where the producer applies the majority of the contracted volume during intervals 13 and 14. Indeed, it can clearly be seen that changes in intervals 13 and 14 have significant impacts on the final offer shown in Figure 4.6. This is also obvious for interval 23. Note that the decisions on contracts 4 and 5 remain unchanged as step 1.

Figure 4.7. The usage distribution of flexible DR in step 1 and 2 - $\rho=0$
Figure 4.8 provides the intervals in which the signed DR options in step 1 are not exercised in the final offer. As can be seen, most of the DR options (DRO) are not exercised during the last intervals. This is more obvious during intervals 42-44, where all four given DRO signed in step 1 are not applied during the final offer. This means that although these DRO agreements are signed in step 1, the wind power producer refuses to use them when the real-time decisions are made. This correction action indeed coincides with the falling trend of the final offer curve during periods 37-48 (See Figure 4.6).

\[\text{Figure 4.8. DR options not exercised in step 2- } \rho=0\]

The outcomes of the most risk-averse wind power producer are delivered in Figures 4.9 and 4.10. The initial and final offers are depicted in Figure 4.9. Similar to the risk-neutral wind power producer, the risk-averse producer makes corrective actions in such a way to increase its offer in the first intervals while reducing it in the last periods. More specifically, the final offer is higher than the initial one during intervals 15 to 19. On the other hand, it can be seen that for intervals 20 to 48 the wind power producer has a lower offer in step 2. Note that the final offer is lower than the expected wind power production in the first 18 intervals (due to selling a portion of energy to the DR aggregator), while it is almost the same as that in the rest of the intervals. Note also that the initial and final offer trends of the risk-averse wind power producer are not much different to the case of the risk-neutral one. This actually indicates how the conservative view of the risk-averse wind power producer affects its initial decisions in step 1.

Figure 4.10 represents the modifications of flexible DR usage in step 2 in comparison to that of the initial decisions. The wind power producer modifies its initial decisions of all flexible DR agreements. This is more obvious in contracts 3 and 4. These modifications are reflected in the final
offer (Figure 4.9), where for instance significant drops in intervals 20-24 shown in the final offer coincide with the higher sale of the wind power producer through flexible DR 4.

Finally note that the risk-averse wind power producer finds all signed DR options in step 1 beneficial and hence exercises them in its final offer.

![Figure 4.9. The initial offer curve (S1) vs. the final offer curve (S2) - \( \rho=5 \)](image)

![Figure 4.10. The usage distribution of flexible DR in step 1 and 2 - \( \rho=5 \)](image)

In the next section of this chapter, the Nordic market is studied and the proposed wind offering strategy for this market is delivered.
4.4. The proposed offering strategy for the Nordic Market

4.4.1. The Proposed Trading Plan

The proposed offering plan is modified to be applicable to the Nordic market, which is a well-established day-ahead market. This market involves three floors, called the spot market, Elbas as an adjustment market and the regulating market [55]. Elbas is not very active [55] and hence it is not modelled here. Therefore, the wind power offering strategy in the Nordic market consists of two steps. In the first step the energy traded in the spot (day-ahead) market is decided while in the second step the production deviation is compensated in the regulating (balancing) market. The proposed offering strategy is illustrated in Figure 4.11.

![Figure 4.11. The proposed wind power offering strategy](image)
Chapter 4. Employing Demand Response by Wind Power Producers

The spot market closes at 12:00pm the preceding day of the energy delivery. Then, offers and bids from players are stacked and the market price is derived. The revenue obtained from the day-ahead (spot) market is formulated in (4.24).

\[ R^{DA}(t,w) = P^{DA}(t) \lambda^{DA}(t,w) d(t) \]  \hspace{1cm} (4.24)

The regulating (balancing) market is used to balance between production and consumption. The balancing market can be either “short” or “long”. In the short state, there is a lack of energy while the long market has excess production [69]. Note that long and short markets are respectively known as positive and negative system imbalances in most studies [56], and thereafter we use these terms in this chapter. In positive systems, regulation down is activated and generators with excess (deficit) generation are paid (charged) at a positive price \( \lambda^{imb, pos} \) (negative price \( \lambda^{imb, neg} \)). On the other hand, in negative system imbalances, regulation up is applied and payments (charges) for excess (deficit) generation are settled at \( \lambda^{imb, pos} \) (\( \lambda^{imb, neg} \)). For each regulation type, the relationships of \( \lambda^{imb, pos} \) and \( \lambda^{imb, neg} \) with the day-ahead market price (\( \lambda^{DA} \)) are given in [56] as follows.

\[ \Downarrow \] \[ \lambda^{imb, pos} \leq \lambda^{DA} \]

\[ \lambda^{imb, neg} \geq \lambda^{DA} \]

This work further extends the given model in such a way that the uncertainty of the regulating market is taken into account:

\[ \lambda^{imb, pos}(t,w) = S^{pos}(w) \lambda^{DA}(t,w) \]  \hspace{1cm} (4.25)

\[ \lambda^{imb, neg}(t,w) = 1.05 \times \lambda^{DA}(t,w) \]  \hspace{1cm} (4.26)

An estimation of imbalance payments and charges for the Nordic market is provided in [70].

\[ \lambda^{imb, pos}(t,w) = 0.95 \times \lambda^{DA}(t,w) \]

\[ \lambda^{imb, neg}(t,w) = 1.05 \times \lambda^{DA}(t,w) \]

This work further extends the given model in such a way that the uncertainty of the regulating market is taken into account:

\[ \lambda^{imb, pos}(t,w) = S^{pos}(w) \lambda^{DA}(t,w) \]  \hspace{1cm} (4.27)

\[ \lambda^{imb, neg}(t,w) = S^{neg}(w) \lambda^{DA}(t,w) \]  \hspace{1cm} (4.28)

where \( S^{pos}(w) \leq 1 \) and \( S^{neg}(w) \geq 1 \) are the scenario-based factors for positive and negative imbalance prices, respectively. Depending on whether the wind power producer has excess or deficit production in the balancing market, it earns revenue or incurs cost. The revenue (payment) or cost (charge) of the balancing market (\( RC^{imb}(t,w) \)) is then formulated below [56].

\[ RC^{imb}(t,w) = P^{pos}(t,w) S^{pos}(t,w) \lambda^{DA}(t,w) d(t) \]

\[ -P^{neg}(t,w) S^{neg}(t,w) \lambda^{DA}(t,w) d(t) \]  \hspace{1cm} (4.29)

56
To include DR in the proposed wind offering strategy for the Nordic market, fixed DR contracts, flexible DR agreements and DR options are taken into account. While fixed DR and flexible DR contracts are formulated in a similar way as those used for the Australian NEM, DR options here are categorized as follows.

Similar to financial options, two DR options are introduced. Type one is called European DR options (EDRO), which is set in a way that the DR agreement is exercised at the expiration time. The expiration time is defined when the contract is arranged. In type 2 however, the DR option can be exercised at any time before the expiration time (American DR option).

DR options in each step are formulated as follows.

**Step 1:** this step indicates whether the DR option is signed or not. This is shown by the binary variable $S_{\text{eo}}(t)$ in the cost functions of European DR Option $\text{eo}$ in (4.30) and $S_{\text{ao}}(t)$ in American DR option $\text{ao}$ in (4.31).

$$
C^{\text{EDRO},S_1}(t) = P_{\text{eo}}(t) \cdot \lambda_{\text{eo}}(t) \cdot S_{\text{eo}}(t) \cdot d(t), \forall \text{eo} = 1,2,...,N_{\text{eo}}
$$  \hspace{1cm} (4.30)

$$
C^{\text{ADRO},S_1}(t) = P_{\text{ao}}(t) \cdot \lambda_{\text{ao}}(t) \cdot S_{\text{ao}}(t) \cdot d(t), \forall \text{ao} = 1,2,...,N_{\text{ao}}
$$  \hspace{1cm} (4.31)

Subscript $\text{eo}$ and $\text{ao}$ denotes European and American DR options, respectively.

**Step 2:** this step belongs to the delivery time in which it is decided whether the signed DR option in step 1 is exercised in step 2 or not. The exercising status of the DR option is shown by a binary variable, where 1 indicates that the contract is applied and zero means that the wind power producer disregards the signed DR option. Indeed this binary variable is shown by $v_{\text{eo}}(t)$ in EDRO (4.32) and $v_{\text{ao}}(t)$ in ADRO (4.33).

$$
C^{\text{EDRO},S_2}(t) = S_{\text{eo}}(t) \cdot \left\{ P_{\text{eo}}(t) \cdot \lambda_{\text{eo}}(t) \cdot v_{\text{eo}}(t) \cdot d(t) + \right\} \cdot (1-v_{\text{eo}}(t)) \cdot f_{\text{eo}}(t), \forall \text{eo} = 1,2,...,N_{\text{eo}}
$$  \hspace{1cm} (4.32)

$$
C^{\text{ADRO},S_2}(t) = S_{\text{ao}}(t) \cdot \left\{ P_{\text{ao}}(t) \cdot \lambda_{\text{ao}}(t) \cdot v_{\text{ao}}(t) \cdot d(t) + \right\} \cdot (1-v_{\text{ao}}(t)) \cdot f_{\text{ao}}(t), \forall \text{ao} = 1,2,...,N_{\text{ao}}
$$  \hspace{1cm} (4.33)

Note that American DR options can be exercised at any time before the expiration time. This constraint is provided in (4.34). This expression shows the period horizon ($t \in T_{\text{ao}}$) in which the American DR option $\text{ao}$ can be exercised.

$$
\sum_{t \in T_{\text{ao}}} v_{\text{ao}}(t) \leq 1; \hspace{0.5cm} \forall \text{ao} = 1,2,...,N_{\text{ao}}
$$  \hspace{1cm} (4.34)
4.4.1.1. Step 1: Day-Ahead Clearing

This step clears on the day-ahead market. The wind power producer decides on day-ahead offers for the entire next day. In addition, the volume of fixed DR contracts is negotiated. Furthermore, the wind power producer determines the periods in which European DR options are signed. Proper American DR options are also signed and the time horizon in which each one can be exercised is determined. Finally, the required flexible DR agreements are appointed.

The above decisions are made while wind power production as well as day-ahead and imbalance prices (charges/payments) are uncertain. A stochastic profit function is formulated in which the uncertain characteristics of these parameters are taken into account using a set of scenarios. In addition, the risk faced with this uncertainty is modelled through CVaR as an appropriate risk measure.

The stochastic profit function is given in (4.35). This function is calculated for the whole day \((t \to 1: FP)\). It consists of the following terms. The expected revenue obtained from selling energy through the day-ahead market, the expected revenue/cost of the balancing market, the costs of all DR contracts and the weighted CVaR.

The profit function is subject to the following constraints. The size of fixed DR and flexible DR contracts are enforced by (4.36) and (4.37), respectively. The positive and negative imbalance offers are limited by (4.38) and (4.39), respectively. The power balance is given in (4.40). In this equation, \(p^{imb}(t,w)\) and \(p^{DR}(t)\) represents the imbalance power and total DR volume, where they are represented in (4.41) and (4.42), respectively. Finally, expressions (4.43) and (4.44) represent CVaR constraints [56], which are derived to linearize this risk measure. Note that \(Profit(w)\) in (4.43) indicates the obtained profit in scenario \(w\) (See Eq. (4.45)).

\[
\text{MAX} \quad PF = \\
\sum_{w \in \Omega} \pi(w) \cdot \left( \sum_{t=1}^{FP} R^{DA}(t,w) + \sum_{ao=1}^{N_{ao}} C^{ADRO,S1}(t) \right) - \sum_{t=1}^{FP} \sum_{eo=1}^{N_{eo}} C^{EDRO,S1}(t) - \sum_{t=1}^{FP} \sum_{f=1}^{N_{FDR}} \sum_{b=1}^{N_{BDR}} C^{FDR}(t) + \sum_{t=1}^{FP} \sum_{f=1}^{N_{flex}} C^{flex,DR,S1}(t) \\
+ \rho \left( \xi - \frac{1}{1-\beta} \sum_{w \in \Omega} \eta(w) \cdot \pi(w) \right)
\]

subject to:

\[
P_{f,b}^{DR,MIN}(t) \leq p_{f,b}^{DR}(t) \leq p_{f,b}^{DR,MAX}(t) \quad (4.36)
\]
\[ P_{DR,MIN}^{\text{flex}}(t) \leq P_{DR}^{\text{flex}}(t) \leq P_{DR,MAX}^{\text{flex}}(t) \]  
(4.37)

\[ 0 \leq P_{\text{pos}}^{\text{flex}}(t,w) \leq P^W(t,w) + P^{TDR}(t) \]  
(4.38)

\[ 0 \leq P_{\text{neg}}^{\text{flex}}(t,w) \leq P^{\text{Inst}W} + P^{TDR}(t) \]  
(4.39)

\[ P^{DA}(t) + P^{\text{imb}}(t,w) = P^W(t,w) + P^{TDR}(t) \]  
(4.40)

\[ P^{\text{imb}}(t,w) = P_{\text{pos}}^{\text{flex}}(t,w) - P_{\text{neg}}^{\text{flex}}(t,w) \]  
(4.41)

\[ P^{TDR}(t) = \sum_{f=1}^{N_{\text{FDR}}} \sum_{b=1}^{N_{\text{BDR}}} P_{f,b}^{\text{DR}}(t) + \sum_{\text{flex}=1}^{N_{\text{Flex}}} P_{\text{flex}}^{\text{DR}}(t) \]  
\[ + \sum_{ao=1}^{N_{ao}} P_{ao}(t) \times Sgn_{ao}(t) + \sum_{eo=1}^{N_{eo}} P_{eo}(t) \times Sgn_{eo}(t) \]  
(4.42)

\[-\text{Profit}(w) + \xi - \eta(w) \leq 0; \forall w = 1, \ldots, N_w \]  
(4.43)

\[ \eta(w) \geq 0; \forall w = 1, \ldots, N_w \]  
(4.44)

\[ \text{Profit}(w) = \sum_{t=1}^{FP} [R^{DA}(t,w) + RC^{\text{imb}}(t,w)] \]  
\[ - \sum_{ao=1}^{N_{ao}} \sum_{t \in T_{ao}} C_{ao}^{\text{ADRO},S1}(t) - \sum_{eo=1}^{N_{eo}} C_{eo}^{\text{EDRO},S1}(t) \]  
\[ - \sum_{f=1}^{N_{\text{FDR}}} \sum_{b=1}^{N_{\text{BDR}}} C_{f,b}^{\text{FDR}}(t) - \sum_{\text{flex}=1}^{N_{\text{Flex}}} C_{\text{flex}}^{\text{FDR},S1}(t) \]  
(4.45)

### 4.4.1.2. Step 2: Regulating (Balancing) Market

Step 2 deals with balancing settlements and final DR approvals. This step runs a successive approach, which is repeated until all periods are covered. For each period a profit function is formulated through which the following decisions are made. The wind power producer decides on its energy trading in the balancing market for the current period. At the same time the producer determines its optimal share of DR agreements for the relevant period. Indeed, each DR agreement that has been set in the previous step is finalized here. The wind power producer decides on the optimal usage of flexible DR. The constraint used here is that the total flexible DR usage should not exceed the agreed volume in step 1. Furthermore, the wind power producer decides on exercising the signed DR options in step 1. In this way, the producer considers that European DR options are exercised only at the expiration time while American DR options can be used at any time before the deadline. Note that the volume of the contracted fixed DR is predetermined in step 1 and cannot be changed in this step.
The above decisions are taken while the day-ahead awards (offers) are known. In addition, the imbalance price and wind power production for the current period are known, but they are still uncertain for the following periods.

The profit function which runs for each period is shown in (4.46). It consists of three terms: the profit obtained from the current period \((t = CP)\) (See Eq. (4.47)), the expected profit over the following intervals until the final period \((t \rightarrow (CP + 1); FP)\) (See Eq. (4.48)) and CVaR. Note that the main terms (4.47) and (4.48) involve the (expected) revenue/cost of the balancing market as well as the costs of DR agreements.

\[
P_F = \text{Prof}(t) \big|_{t=CP} + \text{EProf}(t) \big|_{t=CP+1} + \rho \cdot \text{CVaR} \tag{4.46}
\]

where

\[
\text{Prof}(t) \big|_{t=CP} = RC^{\text{Imb}} (CP) - \sum_{ao=1}^{N_{ao}} C_{ao}^{\text{ADRO},S2} (CP) - \sum_{eo=1}^{N_{eo}} C_{eo}^{\text{EDRO},S2} (CP)
\]

\[
\text{EProf}(t) \big|_{t=CP+1} = \sum_{w \in \Omega} \pi(w) \cdot \sum_{t=CP+1}^{FP} \left[ RC^{\text{Imb}} (t, w) \right] - \sum_{ao=1}^{N_{ao}} \sum_{t \in T_{ao}}^{t \geq CP+1} C_{ao}^{\text{ADRO},S2} (t) - \sum_{t=CP+1}^{FP} \sum_{eo=1}^{N_{eo}} C_{eo}^{\text{EDRO},S2} (t) - \sum_{t=CP+1}^{FP} \sum_{fllex=1}^{N_{fllex}} C_{fllex}^{\text{FlexDR},S2} (t)
\]

The profit function is subject to constraints below.

- Constraints (4.37)-(4.45). Note that in these constraints the day-ahead awards are known.

  In addition, only those DR agreements set in step 1 are taken into account here.

- Flexible DR energy constraint:

\[
\sum_{t=0}^{CP-1} P_{D_{fllex}}^{\text{DR},S2} (t) + \sum_{t=CP}^{FP} P_{D_{fllex}}^{\text{DR},S2} (t) = E_{fllex}^{\text{Agrd}} \quad \forall fllex = 1, \ldots, N_{fllex}
\]

- American DR option constraint (4.34).
4.4.2. Case Study

4.4.2.1. Data Preparation and Assumptions

The proposed plan is evaluated on a realistic case of the Nordic market. Hourly market prices are available [137]. Hence, each period in this section is considered as one hour.

Price scenarios are characterized using ARIMA models. A time series of the spot prices of the Nordic market, spanning January 2012 is used to generate price scenarios [137]. Overall, twenty day-ahead price scenarios are generated in step 1. In addition, four positive and negative imbalance factors are randomly generated. For positive factors, scenarios range between 0.95 and 1 \( (0.95 \leq S^{pos}(w) \leq 1) \), while for negative factors they are between 1 and 1.05 \( (1 \leq S^{neg}(w) \leq 1.05) \).

The wind power producer Hemmet, located in Denmark, is chosen [138]. The installed capacity of this farm is 27MW (Vestas Turbines). Wind speed scenarios are generated using the ARMA model, where the available data in 2012 is used as input time series. Fourteen wind speed scenarios are generated in step 1. These scenarios are then transformed to power scenarios using the Vestas Wind curve [136].

Overall, the total number of generated scenarios is 1120, which is calculated by the product of the numbers for day-ahead prices (20 scenarios), imbalance charges/payments (4 scenario-based factors) and wind power production (14 scenarios).

Figure 4.12 shows the expected day-ahead price and wind power production. The day-ahead price involves two peak periods, just before noon and during the evening. Wind power peaks however occur around midnight and the afternoon.

![Figure 4.12. Average wind power and spot price](image)

In step 2, the day-ahead prices are known. However, wind power production and imbalance prices are still unknown. Wind power scenarios of step 2 are obtained through reducing the number...
of scenarios generated in step 1 to 7 scenarios. Indeed, those scenarios having higher deviations from the expected wind power depicted in Figure 4.12 are removed. This is reasonable as the wind uncertainty in step 2 is lower than that of step 1. Imbalance price scenarios in step 2 are considered the same as the scenarios in step 1.

DR information is as follows. Six fixed DR agreements are considered. The first contract covers 1am to 5am, where the wind power producer sells energy to the DR aggregator. The producer buys fixed DR in the next two contracts (6am-12pm). In fixed DR contract 4, the producer again sells energy to the DR aggregator (1pm-4pm). In the remaining contracts the wind power producer is a fixed DR buyer. Six flexible DR agreements are also modelled. The time horizon for each contract is the same as fixed DR contracts. It is assumed that the wind power producer is able to sell/buy up to 8 MWh flexible DR in each period. Finally, two American and two European DR options are used, where the wind power producer buys these options from the aggregator. The periods in which these options are used are 9am-12pm and 5pm-8pm. The maximum available DR and DR price ranges are provided in Table 4.5.

<table>
<thead>
<tr>
<th>Table 4.5. DR contracts details</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Energy (MWh)</strong></td>
</tr>
<tr>
<td>Buy up to 10</td>
</tr>
<tr>
<td>Sell up to 5</td>
</tr>
</tbody>
</table>

4.4.2.2. Numerical Results and Discussions

A) Decisions in step 1

The given problem is mixed-integer linear programming, which is solved for various risk levels using CPLEX 11.1.1 under GAMS [131].

The expected profit vs. the standard deviation is displayed in Figure 4.13. It is obvious that while the risk-neutral wind power producer gains more profit with the cost of a higher profit deviation, risk-averse producers prefer a lower profit deviation and consequently obtain a lower profit.

Figure 4.14 provides day-ahead offers for various risk levels. The risk-neutral wind power producer sells as much as possible in the day-ahead market. This sale however decreases as the risk level grows. That is, risk-averse producers refuse to sell the majority of their energy in the day-ahead market, where they prefer to sell more energy in the balancing market. This is more obvious for $\rho=1$, where the wind power producer’s sale in the day ahead market is almost zero in most periods. In addition, it can be seen that the offer patterns are very similar in all risk levels. They
follow the peak periods of wind production and day-ahead prices. More specifically, the risk-neutral producer has more noticeable offers during market price peaks.

![Figure 4.13. The expected profit vs. the standard deviation](image1)

![Figure 4.14. The offers in the day-ahead market](image2)

Table 4.6 shows the contracted fixed DR agreements for different levels of the risk. The risk-neutral wind power producer ($\rho = 0$) sets fixed DR contracts (FC) 2 to 6. However, for the risk level of 0.2 and higher, the wind power producer sets FC 2 and FC 4 only. This declining trend is reasonable since the producer is a DR buyer in FC 5 and FC 6, and therefore, as the risk level increases, it avoids taking more risk by buying energy from these contracts and selling it to the volatile day-ahead market.
Table 4.7 represents the periods in which European DR Options (EDRO) are signed in step 1. The risk-neutral wind power producer uses both EDRO 1 and 2 in all periods. However, risk-averse producers refuse to sign EDROs in many periods, where ultimately the most risk-averse producer ($\rho = 1$) only signs EDRO 2 at 6pm. With regards to American DR options (ADRO), the results indicate that both ADRO 1 and 2 are signed in this step.

The volume of flexible DR agreements is illustrated in Table 4.8. Results show that all agreements are used by $\rho = 0.4$. However, for higher risk levels, this share decreases where for $\rho = 1$, flexible DR 2 is not applied. This decrement indeed follows the same rule as fixed DR and DR options.

### Table 4.6. Fixed DR contracts

<table>
<thead>
<tr>
<th>$\rho$</th>
<th>Set Contracts</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>FC2,FC4,FC5,FC6</td>
</tr>
<tr>
<td>0.2</td>
<td>FC2,FC4</td>
</tr>
<tr>
<td>0.4</td>
<td>FC2,FC4</td>
</tr>
<tr>
<td>0.7</td>
<td>FC2,FC4</td>
</tr>
<tr>
<td>1</td>
<td>FC2,FC4</td>
</tr>
</tbody>
</table>

### Table 4.7. Signed European DR options in step 1

<table>
<thead>
<tr>
<th>$\rho$</th>
<th>EDRO1</th>
<th>EDRO2</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>9am-12pm</td>
<td>6pm-8pm</td>
</tr>
<tr>
<td>0.2</td>
<td>9am-12pm</td>
<td>6pm</td>
</tr>
<tr>
<td>0.4</td>
<td>9am</td>
<td>6pm</td>
</tr>
<tr>
<td>0.7</td>
<td>-</td>
<td>6pm</td>
</tr>
<tr>
<td>1</td>
<td>-</td>
<td>6pm</td>
</tr>
</tbody>
</table>

### Table 4.8. Contracted flexible DR in step 1(MWh)

<table>
<thead>
<tr>
<th>$\rho$</th>
<th>Flex1</th>
<th>Flex2</th>
<th>Flex3</th>
<th>Flex</th>
<th>Flex5</th>
<th>Flex6</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>2.5</td>
<td>3</td>
<td>8</td>
<td>6</td>
<td>8</td>
<td>2</td>
</tr>
<tr>
<td>0.2</td>
<td>2.5</td>
<td>3</td>
<td>8</td>
<td>6</td>
<td>8</td>
<td>2</td>
</tr>
<tr>
<td>0.4</td>
<td>2.5</td>
<td>3</td>
<td>8</td>
<td>6</td>
<td>8</td>
<td>2</td>
</tr>
<tr>
<td>0.7</td>
<td>2.5</td>
<td>3</td>
<td>8</td>
<td>4.8</td>
<td>8</td>
<td>2</td>
</tr>
<tr>
<td>1</td>
<td>2.5</td>
<td>0</td>
<td>8</td>
<td>6</td>
<td>8</td>
<td>2</td>
</tr>
</tbody>
</table>

**B) Decisions in step 2**

This section delivers the results of step 2 for the risk-neutral ($\rho = 0$) and the risk-averse ($\rho = 1$) wind producers.

Figures 4.15 and 4.16 depict the offers in the balancing market for $\rho = 0$ and $\rho = 1$, respectively. The sale by the risk-neutral wind power producer is very low in most periods. There
are even some periods in which the producer buys energy from the balancing market. This trend is opposite for the risk-averse producer, where a high amount of power is sold in each period. This outcome confirms the tendency obtained in the day-ahead market shown in Figure 4.14. That is, while the risk-neutral wind power producer is willing to sell more energy in the day-ahead market, the risk-averse producer prefers low risks and consequently submits more energy to the balancing market, where more precise predictions of power production as well as real-time prices are available.

Figure 4.15. Imbalance power for $\rho = 0$

![Figure 4.15](image1.png)

Figure 4.16. Imbalance power for $\rho = 1$

![Figure 4.16](image2.png)

Figure 4.17 provides the total sold power for both wind power producers. The volume is identical for almost all periods. However, it can be seen that the risk-neutral wind power producer
has a higher sale share during the peak periods of the price and wind power production (See Figure 4.12 and Figure 4.17), where this is more evident at 9am, 3pm and 5-10pm. This result indicates that risk-neutral wind power producers have a higher tendency to buy DR than do risk-averse producers.

DR outcomes are as follows. All signed European DR in the first step are exercised in step 2 by both risk-neutral and risk-averse wind power producers. This is also the result for American DR options. Note that in this step, ADRO 1 and 2 are exercised at 9am and 6pm, respectively. This coincides with peak price periods shown in Figure 4.12.

The usage distributions of all flexible DR agreements, except flexible DR 4, are the same as step 1 for both risk levels. The distributions of flexible DR 4 (Flex4) in steps 1 and 2 for the risk-neutral and the risk-averse wind power producers are delivered in Figures 4.18 and 4.19, respectively. In both cases, the wind power producer changes the usage configurations in step 2. It can be seen that in this step the whole flexible DR 4 is used in one period. This is at 3pm for $\rho = 0$ and 1pm for $\rho = 1$. These results confirm a significant difference in sale shares of the risk-neutral and risk-averse wind power producers at relevant hours in Figure 4.17. It can be seen that while the risk-neutral producer has a much higher sale at 3pm, this happens at 1pm for the risk-averse producer.

![Figure 4.17. Total power sold in the market for $\rho = 0$ and $\rho = 1$](image-url)
This chapter presents a new wind offering plan which is adjusted to two different types of electricity markets, i.e. the Australian National Electricity Market (NEM) and the Nordic market. In both plans, a wind power producer is allowed to employ DR to alleviate its production uncertainty as well as market price variations. To include DR, the proposed DR framework in Chapter 3 is used in which the wind power producer can set various DR agreements, called fixed DR, flexible DR,
DR options (in case of the Nordic market, American DR options and European DR options) with DR aggregators.

The main findings are as follows.

a. The proposed two-step plans in both markets allow wind power producers to better place their offers in the market. In the Australian NEM, while the decisions made on the preceding day are taken under uncertainty, step two allows the producer to take corrective actions once uncertain parameters are known. For the Nordic market, risk-neutral and risk-averse producers can determine the level of their participation in the day-ahead and balancing markets. While risk-neutral wind power producers prefer to mostly sell in the day-ahead market, risk-averse producers have a higher share in the balancing market.

b. In the proposed plan, a wind power producer can arrange various DR contracts in step 1 and then manage them in step 2 to better cope with its uncertainty. In this way, they use fixed DR contracts to trade a certain amount of DR. In addition, they benefit from the flexibility of flexible DR contracts, which are manageable in real time. Furthermore, DR options give them a choice to set the contract and wait until real time for the decision on exercising these contracts.

The next chapter will address the behaviour of a DR aggregator in response to energy offering by wind power producers. This is modelled in such a way that a wind power producer has to compete with other DR purchasers to obtain DR from the DR aggregator.

### 4.6. Nomenclature

**A) Indices**

- $b$: Index showing fixed DR’s blocks
- $f$: Index representing fixed DR contracts
- $flex$: Index representing flexible DR agreements
- $ao$: Index representing American DR option
- $eo$: Index representing European DR option
- $o$: Index representing DR options
- $s$: Index representing scenarios in step 2
- $t$: Index representing the time interval
- $w$: Index representing scenarios in step 1
B) Parameters

\( d(t) \)  
Duration of time interval \( t \)

\( FL \)  
Final interval in DR options

\( f_{ao}^{pen}(t) \)  
Penalty of not exercising American DR option \( ao \)

\( f_{eo}^{pen}(t) \)  
Penalty of not exercising European DR option \( eo \)

\( f_o^{pen}(t) \)  
Penalty of not exercising DR option \( o \)

\( p_{DR,MAX}^{fb}(t) \)  
Maximum power of fixed DR \( f, \) block \( b \)

\( p_{DR,MIN}^{fb}(t) \)  
Minimum power of fixed DR \( f, \) block \( b \)

\( p_{flex}^{DR,MAX}(t) \)  
Maximum power of flexible DR \( flex \)

\( p_{flex}^{DR,MIN}(t) \)  
Minimum power of flexible DR \( flex \)

\( P_{ao}(t) \)  
Power of American DR option \( ao \)

\( P_{eo}(t) \)  
Power of European DR option \( eo \)

\( P_o(t) \)  
Power of DR option \( o \)

\( p^w,s_1(t,w) \)  
Wind power production scenario \( w \) in step 1

\( p^w,s_2(t,s) \)  
Wind power production scenario \( s \) in step 2

\( p^W(t,w) \)  
Wind power production scenario \( w \) for the Nordic market case

\( p_{InstW} \)  
Installed wind power capacity for the Nordic market case

\( S^{pos}(t,w) \)  
Scenario-based factors of positive imbalance prices

\( S^{neg}(t,w) \)  
Scenario-based factors of negative imbalance prices

\( \rho \)  
Risk level

\( \beta \)  
Confidence level (Equal to 0.95)

\( \lambda^{DA}(t,w) \)  
Day-ahead market price scenario \( w \)

\( \lambda_{ao}(t) \)  
Price of American DR option \( ao \)

\( \lambda_{eo}(t) \)  
Price of European DR option \( eo \)

\( \lambda_{f,b}^{DR}(t) \)  
Price of fixed DR \( f, \) block \( b \)
Chapter 4. Employing Demand Response by Wind Power Producers

\[ \lambda_{flex}^{DR}(t) \quad \text{Price of flexible DR flex} \]

\[ \lambda_{s.s1}(t,w) \quad \text{Spot price scenario } w \text{ in step 1} \]

\[ \lambda_{s.s2}(t,s) \quad \text{Spot price scenario } s \text{ in step 2} \]

\[ \lambda_{o}(t) \quad \text{Price of DR option } o \]

\[ \pi(w) \quad \text{Probability of scenario } w \text{ in step 1 } (\sum_{w=1}^{N_w} \pi(w) = 1) \]

\[ \pi(s) \quad \text{Probability of scenario } s \text{ in step 2 } (\sum_{s=1}^{N_s} \pi(s) = 1) \]

C) Variables

\[ E_{flex}^{Agrd.s1} \quad \text{Contracted energy volume of flexible DR flex in step 1} \]

\[ p^{DA}(t) \quad \text{Day-ahead wind power cleared in the Nordic market} \]

\[ p^{DR}_{f,b}(t) \quad \text{Power of fixed DR } f, \text{ block } b \]

\[ p^{DR}_{flex.s1}(t) \quad \text{Power of flexible DR flex in step 1} \]

\[ p^{DR}_{flex.s2}(t) \quad \text{Power of flexible DR flex in step 2} \]

\[ p^{pos}(t,w) \quad \text{Positive imbalance wind power} \]

\[ p^{neg}(t,w) \quad \text{Negative imbalance wind power} \]

\[ p^{s.s1}(t,w) \quad \text{Initial power offered in the NEM market} \]

\[ p^{s.s2}(t,s) \quad \text{Final power offered in the NEM market} \]

\[ p^{TDR}(t) \quad \text{Total DR outcome} \]

\[ Sgn_{ao}(t) \quad \text{Binary variable indicating whether American DR option } ao \text{ is signed or not} \]

\[ Sgn_{eo}(t) \quad \text{Binary variable indicating whether European DR option } eo \text{ is signed or not} \]

\[ Sgn_{o}(t) \quad \text{Binary variable indicating whether DR option } o \text{ is signed or not} \]

\[ v_{ao}(t) \quad \text{Binary variable indicating whether American DR option } ao \text{ is exercised or not} \]

\[ v_{eo}(t) \quad \text{Binary variable indicating whether European DR option } eo \text{ is exercised or not} \]

\[ v_{o}(t) \quad \text{Binary variable indicating whether DR option } o \text{ is exercised or not} \]

\[ \xi, \eta(w), \eta(s) \quad \text{Auxiliary variables for calculating CVaR} \]
D) **Numbers and Sets**

- $N_{ao}$: Number of American DR option
- $N_{eo}$: Number of European DR option
- $N_{BDR}$: Number of blocks of fixed DR contracts
- $N_{FDR}$: Number of fixed DR contracts
- $N_{flex}$: Number of flexible DR agreements
- $N_o$: Number of DR options
- $N_w$: Number of scenarios in step 1
- $N_s$: Number of scenarios in step 2
- $T_{ao}$: Set of time period for American DR option
Chapter 5

Modelling Demand Response Aggregator Behaviour in Wind Power Offering Strategy

5.1. Introduction

In Chapter 4, new wind offering strategies were proposed and the effectiveness of the application of demand response (DR) by wind power producers was illustrated.

This chapter assesses the behaviour of a DR aggregator in response to wind power offering strategies. An offering strategy is proposed as follows. A wind power producer decides its offer in the day-ahead market while setting DR contracts with a DR aggregator. The DR aggregator behaviour is modelled through a revenue maximization function in which the aggregator determines its DR trading shares with three main resources: the wind power producer in our study, other market players interested in DR, and the day-ahead market. A bilevel problem is formulated in which the upper-level decision maker (leader) is the wind power producer while the lower-level problem is decided by the DR aggregator (follower). The overall problem is then transformed into a single-level mathematical program with equilibrium constraints (MPEC) by replacing the lower-level problem with its Karush-Kuhn-Tucker (KKT) optimality conditions [139]. In addition, the nonlinearities of the derived MPEC are linearized using the strong duality theorem [139] and the technique provided in [140]. A case study of the Nordic market is used to evaluate the validity of the proposed offering strategy. Uncertainties in each level are characterized using a set of finite scenarios. In addition, the risk is carried out using conditional value-at-risk (CVaR).

1 This chapter covers the following reference:

The rest of the chapter is structured as follows. Section 5.2 addresses the proposed wind offering strategy, where the mathematical formulation of the proposed bilevel problem is described. Then the equivalent linear formulation is presented in Section 5.3. Section 5.4 provides a case study with numerical results. Section 5.5 concludes the chapter. Finally, indices, constants and variables are described in section 5.6.

5.2. The Proposed Wind Offering Strategy

5.2.1. Framework

The following assumptions are made in the proposed strategy. First, it is assumed that the wind power producer makes offers in the day-ahead market while clearing imbalances in the balancing (regulating) market. Additionally, the given wind power producer is treated as similar to conventional power plants [61], where it is responsible for its bidding strategy and power production variation. Moreover, similar to [70], this work determines the optimal offering quantities instead of presenting bidding curves which is investigated in [56]. A further assumption is that modelling technical DR programs through which a DR aggregator obtains DR from customers is not the focus of this study. In addition, for the sake of simplicity this chapter only uses fixed DR as a bilateral contract between the wind power producer and the DR aggregator. Finally, note that the DR flow can be either from the aggregator to players willing to trade DR or in the opposite direction. As a result, the DR aggregator maximizes its revenue when it is a DR seller and minimizes its cost when buying energy through DR contracts.

The proposed bilevel wind offering strategy is illustrated in Figure 5.1. It is considered that the DR aggregator can trade DR with the wind power producer (WPP), other competitors that are willing to trade DR, and the day-ahead market. While parameters in each level are shown by dash line boxes and arrows, decision variables are represented using solid line boxes and arrows. The upper-level problem belongs to the wind power producer (WPP), where it aims to maximize its profit subject to the given constraints as well as the DR volume. Indeed, the obtained DR volume is determined by the DR aggregator in the lower-level problem, where it depends on the price that the wind power producer offers to the aggregator. Thus, the links between the upper-level and lower-level problems are the DR price offered by the wind power producer and consequently, the DR share that the aggregator provides to the wind power producer (double lines in Figure 5.1).

The procedure carried out in this strategy is as follows. The wind power producer determines its DR price while taking into account the DR prices offered by other competitors as well as the day-ahead (DA) market price (refer to the upper-level problem, top right-hand side). Accordingly, the DR aggregator decides the share of each resource in the lower-level problem. Consequently, given
the DR share obtained by the wind power producer, the producer makes its offer in the day-ahead and balancing markets. To this end, besides the price forecasts of DA and Balancing (Bal.) markets, the level of risk taken by the producer is needed to be taken into account (refer to the upper-level problem, bottom left-hand side). That is, depending on how risk averse the producer is, the energy portion to be sold in each market is determined.

![Diagram](image)

**Figure 5.1. The proposed bilevel wind offering strategy**
Chapter 5. Modelling Demand Response Aggregator Behaviour in Wind Offering Strategy

Note that the above decisions are made while the problem is associated with the uncertainty of the following parameters: day-ahead market prices, balancing market prices, wind power production and the DR price offered by other competitors. These uncertain parameters are represented using finite scenarios. Two distinct sets of scenarios are defined in this chapter as follows.

Each upper-level scenario is represented by scenario \( w \), which comprises the vectors of day-ahead price \( \lambda_{DA}(t, w) \), balancing price \( \lambda_{imb}(t, w) \) and wind power production \( P^W(t, w) \).

\[
\text{scenario } w = \{ \lambda_{DA}(t, w), \lambda_{imb}(t, w), P^W(t, w) \}
\]  
(5.1)

The probability of each scenario occurrence equals \( \pi(w) \), where \( \sum_{w=1}^{N_w} \pi(w) = 1 \).

Each lower-level scenario is shown by scenario \( s \), which involves a vector of other competitors’ prices \( \lambda^c(t, s) \) as well as a day-ahead market price vector \( \lambda^{DA}(t, s) \).

\[
\text{scenario } s = \{ \lambda^c(t, s), \lambda^{DA}(t, s) \}
\]  
(5.2)

Similar to the upper-level problem, the probability of each scenario is \( \pi(s) \), where \( \sum_{s=1}^{N_s} \pi(s) = 1 \).

5.2.2. Market Model

The proposed offering plan is applied to the Nordic market.

The day-ahead (spot) market closes at 12:00pm the preceding day of the energy delivery. Then, offers and bids from players are stacked and the day-ahead price is derived. The revenue obtained from the day-ahead market is formulated in (5.3).

\[ R^{DA}(t, w) = p^{DA}(t) \lambda^{DA}(t, w).d(t) \]  
(5.3)

The balancing (regulating) market is used to balance between production and consumption, where regulation up or down is usually activated. Thus, imbalance price \( \lambda^{imb}(t, w) \) is represented by a pair of positive and negative imbalance prices, i.e. \( (\lambda^{imb,pos}(t, w), \lambda^{imb,neg}(t, w)) \). The relationship between imbalance prices (positive \( \lambda^{imb,pos} \) and negative \( \lambda^{imb,neg} \)) and the day-ahead price \( \lambda^{DA} \) during upward and downward regulation is given as follows [56].

\[
\begin{bmatrix}
\lambda^{imb,pos} \\
\lambda^{imb,neg}
\end{bmatrix}
\begin{cases}
\text{Down} \\
\text{Up}
\end{cases}
\begin{bmatrix}
\lambda^{imb,pos} \leq \lambda^{DA} \\
\lambda^{imb,neg} \geq \lambda^{DA}
\end{bmatrix}
\]  
(5.4)
Chapter 5. Modelling Demand Response Aggregator Behaviour in Wind Offering Strategy

An estimation of positive and negative imbalance prices for the Nordic market is provided in [70].

$$\lambda^{imb, pos}(t, w) = 0.95 \times \lambda^{DA}(t, w) \quad (5.5)$$

$$\lambda^{imb, neg}(t, w) = 1.05 \times \lambda^{DA}(t, w) \quad (5.6)$$

As discussed in Chapter 4, we further extend the given model in a way that the uncertainty of the balancing market is taken into account:

$$\lambda^{imb, pos}(t, w) = S^{pos}(t, w) \lambda^{DA}(t, w) \quad (5.7)$$

$$\lambda^{imb, neg}(t, w) = S^{neg}(t, w) \lambda^{DA}(t, w) \quad (5.8)$$

where $S^{pos}(t, w) \leq 1$ and $S^{neg}(t, w) \geq 1$ are the scenario-based factors of positive and negative imbalance prices respectively. The revenue/cost of the balancing market is then formulated below [56].

$$R / C^{imb}(t, w) = P^{pos}(t, w) S^{pos}(t, w) \lambda^{DA}(t, w) d(t) - P^{neg}(t, w) S^{neg}(t, w) \lambda^{DA}(t, w) d(t) \quad (5.9)$$

5.2.3. Objective Function

The bilevel problem is formulated as follows:

Maximize \( PF = \)

$$\sum_{w=1}^{N_w} \pi(w) \sum_{t=1}^{T} \left( R^{DA}(t, w) + R / C^{imb}(t, w) \right) - \sum_{t=1}^{T} P^{DR}(t) \lambda^{DR}(t) + \rho \left( \xi - \frac{1}{1-\beta} \sum_{w=1}^{N_w} \eta(w) \pi(w) \right) \quad (5.10)$$

Subject to

1. $$0 \leq P^{pos}(t, w) \leq P^{W}(t, w) + P^{DR}(t) \quad (5.11)$$
2. $$0 \leq P^{neg}(t, w) \leq P^{InstW} + P^{DR}(t) \quad (5.12)$$
3. $$P^{DA}(t) + P^{imb}(t, w) = P^{W}(t, w) + P^{DR}(t) \quad (5.13)$$
4. $$P^{imb}(t, w) = P^{pos}(t, w) - P^{neg}(t, w) \quad (5.14)$$
5. $$-\text{Profit}(w) + \xi - \eta(w) \leq 0; \forall w = 1, \ldots, N_w \quad (5.15)$$
6. $$\eta(w) \geq 0; \forall w = 1, \ldots, N_w \quad (5.16)$$
7. $$\text{Profit}(w) = \sum_{t=1}^{T} \left( R^{DA}(t, w) + R / C^{imb}(t, w) \right) - \sum_{t=1}^{T} P^{DR}(t) \lambda^{DR}(t) \quad (5.17)$$
Chapter 5. Modelling Demand Response Aggregator Behaviour in Wind Offering Strategy

\[ P^{DR}(t) = C^{DR,T}(t) \sum_{s=1}^{N} \pi(s).sp^w(t,s) \]  
\[ C^{DR,T}(t) = P^{\max,s}(t)b^s(t) - P^{\max,b}(t)b^b(t) \]

where,

\[ \text{sp}^w(t,s) \in \arg \max \left\{ \sum_{s=1}^{N} \pi(s).C^{DR,T}(t) \left[ sp^w(t,s)A^{DR}(t) + sp^{DA}(t,s)A^{DA}(t,s) + \sum_{c=1}^{N} sp^c(t,s)A^{c}(t,s) \right] \right\} \]

\[ sp^w(t,s) + sp^{DA}(t,s) + \sum_{c=1}^{N} sp^c(t,s) = 1 \quad \text{if } \{ b^s(t) = 1 \text{ or } b^b(t) = 1 \} : \gamma(t,s) \]

\[ sp^w(t,s), sp^{DA}(t,s), sp^c(t,s) \geq 0 \quad \forall t,s,c : \mu^w(t,s), \mu^{DA}(t,s), \mu^c(t,s) \]

The upper level problem indicates the profit maximization of the wind power producer (Eq. (5.10)). This problem involves the expected revenue obtained from the day-ahead market, the expected revenue/cost of the balancing market, the cost of DR and the risk measure. \( \beta \) is the confidence level, which is 0.95. Note that the risk level \( (\rho = [0, -\infty]) \) represents a trade-off between the expected profit and the risk.

The profit function is subject to the following constraints. Positive and negative imbalance offers are limited by (5.11) and (5.12), respectively. The power balance is given in (5.13). In this equation, \( P^{imb}(t,w) \) is the power traded in the balancing market, which is represented in (5.14). Expressions (5.15) and (5.16) represent conditional value at risk (CVaR) constraints [56] which are derived to linearize this risk measure. Note that Profit \( (w) \) in (5.17) indicates the obtained profit in scenario \( w \). The DR volume is calculated in (5.18). \( C^{DR,T}(t) \) is the total available DR capacity that can be traded by the aggregator. As mentioned earlier the DR flow can be either from the DR aggregator to the wind power producer or in the reverse direction. Therefore, the DR capacity is the maximum DR that the aggregator can either sell \( (P^{max,s}(t)) \) or buy \( (P^{max,b}(t)) \) (See Eq. (5.19)). \( b^s(t) \) and \( b^b(t) \) are binary parameters which respectively indicate whether the DR aggregator is a DR seller or buyer in time period \( t \).

\[ sp^w(t,s) \] is the DR share percentage that the wind power producer trades with the DR aggregator. Indeed, this share is obtained by the lower level problem which is formulated in (5.20)-(5.22). The revenue maximization problem of the DR aggregator is modelled in (5.20). The DR aggregator trades DR with the wind power producer, the day-ahead market and other competitors. Note that \( sp^{DA}(t,s) \) represents the DR share percentage of the day-ahead market and \( sp^c(t,s) \)
shows the share of competitor \( c (c = 1,2, ..., N_{TC}) \). Note also that during periods in which the aggregator is a DR buyer, the objective is a cost minimization function. Constraint (5.21) imposes that total DR share percentage must be equal to 1. Finally, constraint (5.22) is used for variable declarations. Note that dual variables for constraints (5.21) and (5.22) are \( \gamma(t,s), \mu^w(t,s), \mu^{DA}(t,s) \) and \( \mu^c(t,s) \), which are indicated following a colon.

### 5.3. Linear Formulation

The given approach is a bilevel programming problem that includes nonlinearity. This section provides an equivalent single-level linear problem which is easily solvable by commercially available software. The following procedure is applied for this purpose.

First, the bilevel problem is transformed into a single-level mathematical program with equilibrium constraints (MPEC). For this purpose, the lower-level problem is replaced by its first-order optimality conditions through the KKT conditions. Note that this transformation is valid since the lower-level problem is continuous and linear and thus convex.

To make the lower-level problem in a standard form, we can replace the maximization function by a negative minimization function. Then, the Lagrangian function of the lower-level problem is given as:

\[
L = -\sum_{s=1}^{N_t} \pi(s).C^{DR,T}(t) \left[ sp^w(t,s).\lambda^{DR}(t)sp^{DA}(t,s)\lambda^{DA}(t,s) + \sum_{c=1}^{N_{TC}} sp^c(t,s)\lambda^c(t,s) \right] \\
- \gamma(t,s) \left[ sp^w(t,s) + sp^{DA}(t,s) + \sum_{c=1}^{N_{TC}} sp^c(t,s) - 1 \right] \\
- \mu^w(t,s)sp^w(t,s) - \mu^{DA}(t,s)sp^{DA}(t,s) - \mu^c(t,s)sp^c(t,s) 
\]

In this function, \( \gamma(t,s), \mu^w(t,s), \mu^{DA}(t,s) \) and \( \mu^c(t,s) \) are the relevant Lagrangian multipliers of the lower-level constraints. Accordingly, KKT conditions associated with the lower-level problem are obtained as follows.

\[
\frac{\partial L}{\partial sp^w(t,s)} = -\sum_{s \in \Omega_s} \pi(s).C^{DR,T}(t)\lambda^{DR}(t) - \gamma(t,s) - \mu^w(t,s) = 0 
\]

(5.24)

\[
\frac{\partial L}{\partial sp^{DA}(t,s)} = -\sum_{s \in \Omega_s} \pi(s).C^{DR,T}(t)\lambda^{DA}(t,s) - \gamma(t,s) - \mu^{DA}(t,s) = 0 
\]

(5.25)

\[
\frac{\partial L}{\partial sp^c(t,s)} = -\sum_{s \in \Omega_s} \pi(s).C^{DR,T}(t)\lambda^c(t,s) - \gamma(t,s) - \mu^c(t,s) = 0 \quad \forall c = 1, ..., N_{TC} 
\]

(5.26)

\[
\mu^w(t,s), \mu^{DA}(t,s), \mu^c(t,s) \geq 0 \quad \forall t, s, c 
\]

(5.27)

\[
\mu^w(t,s)sp^w(t,s) = 0 
\]

(5.28)
\[
\mu^{DA}(t,s)sp^{DA}(t,s) = 0 \quad (5.29)
\]
\[
\mu^{\bar{c}}(t,s)sp^{\bar{c}}(t,s) = 0 \quad \forall c = 1,\ldots,N_{TC} \quad (5.30)
\]

Note that (5.27)-(5.30) are complementarity conditions. Equations (5.28)-(5.30) make the problem nonlinear. The next step is to linearize the nonlinear complimentary conditions resulting from applying KKT.

With the cost of adding extra binary variables, the complementarity slackness conditions can easily be linearized as follows [140].

\[
sp^{w}(t,s) \leq M^{sp}v^{w}(t,s) \quad (5.31)
\]
\[
sp^{DA}(t,s) \leq M^{sp}v^{DA}(t,s) \quad (5.32)
\]
\[
sp^{c}(t,s) \leq M^{sp}v^{c}(t,s) \quad \forall c = 1,\ldots,N_{c} \quad (5.33)
\]
\[
\mu^{w}(t,s) \leq M^{\mu}(1-v^{w}(t,s)) \quad (5.34)
\]
\[
\mu^{DA}(t,s) \leq M^{\mu}(1-v^{DA}(t,s)) \quad (5.35)
\]
\[
\mu^{\bar{c}}(t,s) \leq M^{\mu}(1-v^{\bar{c}}(t,s)) \quad \forall c = 1,\ldots,N_{c} \quad (5.36)
\]

where \(M^{sp}\) and \(M^{\mu}\) are sufficiently large constants and \(v^{w}(t,s), v^{DA}(t,s)\) and \(v^{\bar{c}}(t,s)\) are binary variables.

Finally, we need to derive the linear form of the product of \(P^{DR}(t)\) and \(\lambda^{DR}(t)\) in (5.10). For this purpose, the strong duality theorem [139] is used here. The dual of the lower-level problem for the upper-level variable \(\lambda^{DR}(t)\) is given in (5.37). Note again that we replace the maximization function in the lower-level problem by a minus minimization function to have it in a standard form.

\[
\text{Maximize} \quad \sum_{s=1}^{N_{s}} \pi(s)\gamma(t,s) \quad (5.37)
\]

\(\gamma(s,t)\) is the dual variable of the lower-level equality (5.21). According to the strong duality theorem, the values of primal objective function (5.20) and the dual function (5.37) must be equal at the optimal solution. That is:

\[
\sum_{s=1}^{N_{s}} \pi(s)\gamma(t,s) = -\sum_{s=1}^{N_{s}} \pi(s)C^{DR,T}(t)[sp^{w}(t,s)\lambda^{DR}(t) + sp^{DA}(t,s)\lambda^{DA}(t,s) + \sum_{c=1}^{N_{TC}} sp^{c}(t,s)\lambda^{c}(t,s)] \quad (5.38)
\]

Given the above expression and also from (5.18), the product of \(P^{DR}(t)\lambda^{DR}(t)\) is obtained:
This product is now linear and can be used in the equivalent single-level objective function.

Overall, the equivalent single-level linear program is as:

Maximize \( PF = \)

\[
\sum_{w=1}^{N_w} \pi(w) \left[ T \sum_{t=1}^{T} \left( R^{DA}(t, w) + R / C^{Imb}(t, w) \right) - \sum_{t=1}^{T} \left( -\sum_{s=1}^{N_s} \pi(s) \gamma(t, s) + C^{DR,T}(t) \left( s^{DA}(t, s) \lambda^{DA}(t, s) + \sum_{c=1}^{N_{TC}} s^{C}(t, s) \lambda^{C}(t, s) \right) \right) \right] + \rho \left( \xi - \frac{1}{1 - \beta} \sum_{w=1}^{N_w} \eta(w) \pi(w) \right)
\]

subject to

Constraints (5.11)-(5.19) and (5.21)-(5.22).

Constraints (5.24)-(5.27).

Constraints (5.31)-(5.36)

The derived problem is a mixed-integer linear programming approach.

5.4. Case Study

5.4.1. Data Preparation and Assumptions

The proposed offering strategy is assessed on a realistic case of the Nordic market. Since hourly market prices are available [137] each period is considered as one hour. Nevertheless, the presented strategy is also applicable on shorter time horizons.

The upper-level scenarios are generated as follows. Ten price scenarios are generated. For this purpose, the ARIMA method is used. A time series of spot prices of the Nordic market spanning January 2012 are used to generate price scenarios [137]. In addition, four positive and negative imbalance factors are randomly generated. For positive factors, scenarios range between 0.95 and 1 (0.95 \( \leq S^{pos}(t, w) \leq 1 \)), while for negative factors, they are between 1 and 1.05 (1 \( \leq S^{neg}(t, w) \leq 1.05 \)).
The wind power producer Hemmet located in Denmark is chosen [138]. The installed capacity of this farm is 27MW (Vestas Turbines). Wind speed scenarios are generated using the ARMA model where the available data in 2012 is used as an input time series. Accordingly, fourteen wind speed scenarios are generated. These scenarios are then transformed into power scenarios using the Vestas Wind curve. The overall number of scenarios makes a trade-off between the tractability of the problem and the accuracy of the results [93]. Note that using wind speed and market price data for a longer period will improve the accuracy of the generated scenarios. However, due to the limited access to wind speed data, this study uses short-period data, i.e. January 2012. Note also that for making a better correlation between wind power and market price scenarios, the period of price data is chosen to be the same as wind speed data.

Figure 5.2 shows the expected day-ahead price and wind power production. The day-ahead price involves two peak periods, just before noon and during the evening. Wind power peaks however, occur during midnight and the afternoon.

![Figure 5.2. Average wind power and spot price](image)

The lower-level scenarios are generated as follows. Besides the wind power producer, two other competitors (C1 and C2) willing to trade DR with the aggregator are considered. Three price scenarios are generated for each competitor as illustrated in Figure 5.3. Competitors are indicated with “C”, while “S” represents the scenarios. Note that these scenarios are generated in a way that they are closed to the day-ahead market price mean shown in Figure 5.2. Indeed, the DR aggregator determines the DR share of each individual competitor based on these price scenarios. Note also that day-ahead price scenarios for the lower-level problem are the same as those generated in the upper-level one.
This work assumes the DR data as follows. The maximum DR potential that the DR aggregator can either buy or sell in each period is assumed to be 10 MW. The aggregator is assumed to be a DR buyer from 2am to 5am and a seller from 9am to 12pm and 5pm to 9pm.

5.4.2. Numerical Results

The given mixed integer programming approach is solved for various risk levels using CPLEX 11.1.1 under GAMS [131].

Figure 5.4 depicts the expected profit versus the standard deviation for the given risk levels. The risk-averse wind power producer (\( \rho = 2 \)) obtains the expected profit of $16,560 with a deviation of $7,740. As the producer becomes more of a risk taker (i.e. the risk level decreases), both the expected profit and the standard deviation grow. This is more obvious for the risk-neutral wind power producer (\( \rho = 0 \)), where the expected profit and its deviation are $16,713 and $8,000, respectively. In other words, the risk-neutral wind power producer obtains 1% higher profit than the risk-averse one with a cost of 3.4% higher profit deviation.
Figures 5.5 and 5.6 show the bids placed into the day-ahead market and the power exchanged in the balancing market, respectively. While the risk-neutral wind power producer places the majority of its energy offer into the day-ahead market (See Figure 5.5), its offer in the balancing market is low and even negative in some periods (See Figure 5.6). That is, the risk-neutral producer takes risk in some periods to bid higher than its energy production with the hope of buying that amount in the balancing market at a cheaper cost. This trend is more obvious at hours 16-18 where at each hour the wind power producer has to buy more than 5MW from the balancing market to compensate its high offer in the day-ahead market.

Increasing the risk level causes a significant drop in the day-ahead market bids. For instance, while the producer with risk level $\rho = 0.5$ has a reasonable day-ahead sale share during its peak production, the shares of the most risk-averse wind power producers ($\rho = 1.5$ and $\rho = 2$) are almost negligible in the day-ahead market. Indeed, risk-averse producers sell the majority of their energy into the balancing market. This trend is reasonable since the risk-averse producers refuse to take more risk by selling their energy into the day-ahead market while their production and also the market price are associated with a significant level of uncertainty. Thus they choose the balancing market where they are close to real time and have a better forecast of their production as well as the market price.
The DR volumes obtained by the wind power producer in various risk levels are illustrated in Figure 5.7. The wind power producer sells DR to the aggregator at 2-5am and buys DR at 9am-12pm and 5-9pm. Risk taker wind power producers have a high sale share through DR. This is particularly evident for the risk-neutral producer, where its DR sales for 3am and 4-5am are 5MW and 4MW, respectively. This share however decreases for risk-averse wind power producers. More specifically, this falling trend is significant for the risk levels $\rho = 1.5$ and $\rho = 2$ during the period 3-5am. It can be seen that the DR sale decreases to less than 2 MW in these periods. This declining trend is sensible since risk-averse producers tend to sell the majority of their energy through the
balancing market where they have a better forecast of their production as well as the market price (see Figure 5.6). Hence, selling energy through DR on the day prior to the energy delivery can increase their risk as they may face power shortages in the delivery time and consequently not be able to meet the sold power through DR.

During the periods in which the wind power producer is a DR buyer, i.e. 9-12pm and 5-9pm, the risk-neutral producer buys more DR than the risk-averse one. It can be seen that during most hours, the risk-neutral producer buys around 2 MW DR from the aggregator. However, increasing the risk level is followed by a decreasing tendency in most hours. This is more apparent at 10am, 12, 8 and 9 pm where the share of DR procurement by risk-averse wind power producers, particularly in the risk levels $\rho = 1.5$ and $\rho = 2$ is almost negligible. This tendency is true since buying energy from DR in a fixed cost and selling it into the volatile market increases the risk of risk-averse wind power producers and hence, they may avoid this practice.

![Figure 5.7. DR obtained by the wind power producer](image)

Figure 5.8 shows the DR prices offered by the wind power producer at various risk levels. In addition, DR price scenarios by other competitors (Shown in Figure 5.3) are also depicted in this figure to provide a better comparison. Note that competitors are indicated with “C”, while “S” represents the scenarios. The risk-neutral wind power producer offers around $1/MWh lower price than the risk-averse producers at 3-5am. This lower price indeed resulted in a higher sale share shown in Figure 5.7. For the rest of the periods in which the wind power producer buys DR from the aggregator this inclination is reversed. Actually, the risk-neutral producer offers higher prices to procure more DR as depicted in Figure 5.7. For instance, this producer gives around $1.5/MWh higher than risk-averse producers at 10-11am and 8-9pm. In comparison with other competitors, the
DR prices given by the wind power producers are low in the first period covering 2-5am. However, for the remaining periods, wind power producers offer DR prices close to the other competitors.

Figure 5.8. The DR price offered by the wind power producer

Figure 5.9 depicts the total DR share of both competitors together as well as the day-ahead market. Note that as mentioned earlier the periods in which DR is traded are as follows. Period 1 is 2-5am, period 2 represents 9am-12pm and period 3 covers 5-9pm. Obviously there is an opposing DR trend as compared to that of the wind power producer. That is, as the risk level increases, particularly for \( \rho = 2 \), the DR aggregator buys more DR from these resources during the time period 2-5am (period 1). In addition, during the periods in which the aggregator is a DR seller, i.e. periods 2 and 3, its sale share increases as the risk level grows. This trend is more clarified in Table 5.1, where the DR volumes (MWh) for each competitor, i.e. C1 and C2, as well as the day-ahead market (DA) in risk levels \( \rho = 0 \) and \( \rho = 2 \) are distinctly provided. It can be seen that in both risk levels, the DR share of the day-ahead market is higher than other competitors. In addition, it is obvious that while the aggregator refuses to buy DR from C1 and C2 in \( \rho = 0 \) at 3-5am, it buys more than 1 MW for \( \rho = 2 \) at each relevant hour.
5.4.3. Sensitivity Analysis

This section evaluates the impact of power production uncertainty on the proposed strategy. A deterministic case (Case1) is compared with the current study in the chapter (Case2). Indeed, the expected wind power production, shown in Figure 5.2, is considered as the wind power input in the deterministic case. The day-ahead offers by the risk-neutral and risk-averse wind power producers are illustrated in Figures 5.10 and 5.11. Further results are as follows. Both risk-neutral and risk-averse producers have no participation in the balancing market when their production is known (Case1). The risk-neutral producer has exactly the same DR trading in both cases. However, DR trading by the risk-averse producer is different in case 1 to case 2 (See Figure 5.12).
The main findings from Cases 1 and 2 are as follows.

1- As can be seen from Figure 5.10, the day-ahead offer by the risk-neutral wind producer mostly follows its expected production in Case 1, where the producer perfectly knows its production. Indeed, the differences are as a result of DR trading since the producer in Case 1 has no involvement in the balancing market. On the other hand, it is obvious that when the producer has uncertain power production, its day-ahead offer significantly changes due to that uncertainty. Actually, the producer has to compensate this deviation in the balancing market (Refer to Figure 5.6).

2- An interesting point is interpreted for the risk-averse wind power producer. It can be seen from Figure 5.11 that the risk-averse wind power producer mostly prefers to sell through the day-ahead market if its production is perfectly known (Case 1). This is in contrast to Case 2, where the wind power production is faced with uncertainty and thus, the risk-averse producer mainly prefers to participate in the balancing market due to its better production forecast in that market.

3- The risk-averse wind power producer sells more energy through DR in Case 1 than Case 2 (See period 1 in Figure 5.12). This is reasonable since the power production in Case 1 is deterministic and therefore, the producer can hedge against the risk of the market by selling a portion of its energy through the bilateral DR contract. Note that the producer behaviour in buying DR is arbitrary (Periods 2 and 3 in Figure 5.12). This is mainly because of two opposite aims: on one hand, the risk-averse producer is not interested in buying DR to sell it in the volatile market; on the other hand, the producer may find some periods in which buying DR is beneficial as there may be a chance of increasing its profit. This happens in period 3, where the market price is at its peak (See the expected day-ahead price in Figure 5.2).
Chapter 5. Modelling Demand Response Aggregator Behaviour in Wind Offering Strategy

Figure 5.11. Day-ahead offers by the risk-averse wind power producer: Cases 1 and 2

Figure 5.12. DR trading by the risk-averse wind power producer: Cases 1 and 2
5.5. Summary

This chapter models the DR aggregator behaviour in wind offering strategies. A bilevel problem is formulated which is then transformed into a single-level linear programming approach through proper techniques in order to make it solvable using commercially available software such as GAMS.

The overall problem is a stochastic programming approach in which the risk is carried out using CVaR. A case of the Nordic Market is chosen to assess the validity of the given problem. The main findings are as follows.

1. While risk-neutral wind power producers mostly sell their energy in the day-ahead market, risk-averse producers mainly choose the balancing market to participate in.
2. The wind power producer can buy DR during the peak price periods to lessen the risk of its power production and market price uncertainty. On the other hand, the producer is able to sell some portion of its energy through DR contracts with the aggregator during off-peak periods.
3. While the risk-neutral wind power producer has a higher share in DR trading, either in selling or in buying, the risk-averse producers mostly refuse to be involved in DR.
4. Modelling the DR aggregator behaviour makes DR trading more competitive since the wind power producer is required to compete with other players to offer a reasonable DR price to the DR aggregator.
5. The uncertainty of wind power production affects day-ahead offers of both risk-neutral and risk-averse wind power producers, particularly the latter.

The next Chapter will further extend the study in this chapter to address the DR application by wind power producers with significant wind power production, which are able to exercise market power in day-ahead markets.

5.6. Nomenclature

A) Indices

- $c$: Index of competitors interested in trading DR
- $s$: Index of scenario in the lower-level problem
- $t$: Index representing the time interval
- $w$: Index of scenario in the upper-level problem

B) Parameters
$b^b(t)$ Binary parameter indicating whether the DR aggregator is a DR buyer

$b^s(t)$ Binary parameter indicating whether the DR aggregator is a DR seller

$C^{DR.T}(t)$ Available DR capacity (MW)

d$(t)$ Duration of period $t$

$\dot{\lambda}^C(t,s)$ Other competitors’ price for DR

$\lambda^{DA}(t,s)$ Day-ahead price scenario in the lower-level problem

$\lambda^{DA}(t,w)$ Day-ahead price scenario in the upper-level problem

$\lambda^{imb}(t,w)$ Imbalance price scenario

$\lambda^{imb,neg}(t,w)$ Negative imbalance price scenario

$\lambda^{imb,pos}(t,w)$ Positive imbalance price scenario

$p^{\max,b}(t)$ Maximum DR capacity that the DR aggregator can buy

$p^{\max,s}(t)$ Maximum DR capacity that the DR aggregator can sell

$p_{InstW}$ Installed capacity of the wind power producer

$p^W(t,w)$ Wind power production scenario

$S^{pos}(t,w)$ scenario-based factors of positive imbalance prices

$S^{neg}(t,w)$ scenario-based factors of negative imbalance prices

$\pi(w), \pi(s)$ Probability of scenario $w$/ scenario $s$

**C) Variables**

$p^{DA}(t)$ Day-ahead power sold by the wind power producer

$p^{DR}(t)$ DR procured by the wind power producer

$p^{pos}(t,w)$ Positive imbalance wind power

$p^{neg}(t,w)$ Negative imbalance wind power

$sp^{DA}(t,s)$ DR share in the day-ahead market

$sp^{c}(t,s)$ DR share of competitor $c$

$sp^w(t,s)$ DR share percentage by the wind power producer
Chapter 5. Modelling Demand Response Aggregator Behaviour in Wind Offering Strategy

\[ \lambda_{DR}(t) \]  
DR price offered by the wind power producer

\[ \gamma(t,s), \mu^w(t,s), \mu^c(t,s) \]  
Dual variable relevant to the lower-level problem

\[ \xi, \eta(w) \]  
Auxiliary variables for calculating CVaR

**D) Numbers and Sets**

\[ N_s \]  
Number of scenarios in the lower-level problem

\[ N_{TC} \]  
Number of total consumers

\[ N_w \]  
Number of scenarios in the upper-level problem

\[ T \]  
Set for time duration
Chapter 6
Demand Response Application by Strategic Wind Power Producers

6.1 Introduction

Significant wind power penetration brings new challenges into electricity markets. One important issue is that a wind power producer with high power production may become dominant in the market. In this way, the wind power producer may play strategically to change the market price. A few investigations have recently raised this issue. Reference [79] is the most comprehensive one. The authors investigate high penetration of a wind producer by modelling it as a strategic player in both day-ahead and balancing markets. An equilibrium problem with equilibrium constraints (EPEC) is formulated. The authors in [12] consider a wind power producer, which is a price maker in the day-ahead market and a deviator in the balancing market. Unlike [12], a wind power producer in [80] is fully competitive in the day-ahead market while having market power in the balancing market. The authors in [81] investigate the effect of a price-maker wind power producer on the market price.

This Chapter studies a strategic wind power producer which is responsible for its participation in the market and also uses DR to lessen the risk of its production as well as balancing market price uncertainties. An offering strategy for this producer is proposed as follows. The producer offers into the day-ahead market. It is assumed that the wind power producer is the only player with market power in this market while other participants are fully competitive. Consequently, a day-ahead market is cleared through which the wind producer can determine its power level and price in this

---

market. In addition, the wind power producer uses DR to alleviate its power production deviation in real-time dispatch. To this end, the strategic wind power producer bilaterally sets a DR contract with a DR aggregator. The DR aggregator itself seeks to maximize its revenue from selling the DR product through three purchasers, namely the wind power producer in this chapter, the day-ahead market, and other players willing to purchase DR. The above problem is formulated in a bilevel approach, which is then transformed into a single level linear program and solved on a realistic case of the Nordic Market.

The Chapter is structured as follows. First, the proposed offering strategy by a strategic wind power producer is discussed. Then, the problem formulation is presented in section 6.3. This problem is a bilevel approach which is transformed to a single-level linear problem in the next section. Section 6.5 provides the case study and results. Conclusions are drawn in section 6.6. Finally, the indices, variables and parameters used in the chapter are explained in the nomenclature in the last section.

6.2 Strategic Wind offering

6.2.1 Framework

The following assumptions are considered. For the sake of simplicity, we assume the strategic behaviour of a wind power producer in the day-ahead market only. This is reasonable as the majority of energy is traded in this market [12]. Note that exercising of market power by power plants including wind power producers may happen in any electricity markets. This is due to different circumstances, where one reason for exercising market power by wind power producers is their high power penetration. For instance, as reported in [134], the Danish Elspot areas, DK1 and DK2, had negative prices for 39 and 30 hours respectively in 2013, due to high wind power production. In addition, a study on the Nordic market [82] shows that producers with fluctuating production such as wind producers may act strategically in their bidding on the spot market due to the asymmetric cost of the regulating market. Note also that the assumption of owning high wind power production by a wind power producer is realistic as there are some real cases which the coordination of several wind farms is recommended as a solution to alleviate their production deviation [81, 141].

In addition, the transmission network is not modelled in this chapter, which makes the findings intuitive. This is a common assumption in wind offering studies such as [14, 56, 66]. Nevertheless, network constraints can be modelled in a similar way to [12]. In addition, the balancing market is assumed to be settled in a single-price system, which is used in the US, instead of a dual-price
scheme. Furthermore, similar to the existing studies, a single one hour period is chosen. However, the problem is also valid for multi period problems.

The proposed problem is depicted in Figure 6.1. Note that parameters in each level are shown by dash line boxes and arrows, while the decision variables are represented using solid line boxes and arrows. In addition, the links between different levels of the problem are indicated by double lines.

The procedure carried out in this bilevel problem is as follows. In the upper-level problem, the wind power producer (WPP) makes two decisions: D1) the day-ahead offer; D2) the DR price given to the DR aggregator. The day-ahead (DA) offer includes the energy volume and price for each dispatch interval. This decision is faced with the uncertainty involved in power production and imbalance price forecasts. Therefore, plausible realizations of these stochastic parameters are required to be taken into account. In addition, the level of the risk taken by the producer affects the DA offer decision. That is, the sale share of day-ahead and balancing markets may change in various risk levels. The day-ahead energy volume and price as well as the DR share procured by the wind power producer are the other factors that affect the DA offer. The former, i.e. the day-ahead energy volume and price, is decided in the lower-level problem 1 through a market clearing process. Offers from the wind power producer as well as other generators and the DR aggregator are stacked. On the other hand, demand bids are also received. Consequently, the day-ahead market price and energy volume are determined from the intersection of supply and demand curves (See the lower-level problem 1). The latter, i.e. the DR share procured by the wind power producer, is decided in the lower-level problem 2. In a revenue maximization problem, the DR aggregator determines the DR share to be sold to three DR purchasers: the wind power producer, other DR buyers and the day-ahead market. This decision is made according to the prices offered by the DR purchasers. Note that the DR price offered by the wind power producer is decided in the upper level problem as decision 2 (D2). The wind power producer decides on this price based on the day-ahead price (derived in the lower-level problem 1) and an anticipation of DR prices offered by other DR purchasers (see the upper-level problem, right-hand side). Note that trading DR through bilateral contracts exists in the real case [142]. In addition, DR aggregators can directly participate in some markets such as PJM [143].
Figure 6.1. Strategic wind offering considering the DR aggregator behaviour
6.2.2 Uncertainty Characterization

Each upper-level scenario is represented by scenario \( w \), which comprises a vector of imbalance prices \( \lambda_{imb}(t,w) \) and wind power production \( P_{WP}(t,w) \).

\[
\text{scenario } w = \{ \lambda_{imb}(t,w), P_{WP}(t,w) \}
\]  

(6.1)

The probability of each scenario occurrence equals \( \pi(w) \), where \( \sum_{w=1}^{N_w} \pi(w) = 1 \).

Each scenario in the lower-level problem 2 is illustrated by scenario \( s \), which involves a vector of other competitors’ DR prices \( \lambda^C(c,t,s) \).

\[
\text{scenario } s = \{ \lambda^C(c,t,s) \}
\]  

(6.2)

Similar to the upper-level problem, the probability of each scenario is \( \pi(s) \), where \( \sum_{s=1}^{N_s} \pi(s) = 1 \).

Note that the lower-level problem 1 is a deterministic problem and independent of scenarios.

6.3 Problem Formulation

The bilevel problem is formulated as follows.

Maximize

\[
\sum_{wu=1}^{N_{wu}} P_{WDA}(wu,t) \lambda^{DA}(t) - P_{DR}(t) \lambda^{DR}(t) + \sum_{w=1}^{N_w} \pi(w) P_{imb}(t,w) \lambda_{imb}(t,w) \\
+ \rho \left[ (1 - \beta) \sum_{w=1}^{N_w} \eta(w) \pi(w) - \epsilon \right], \forall t
\]  

(6.3)

Subject to

\[
\sum_{wu=1}^{N_{wu}} P_{WDA}(wu,t) + P_{imb}(t,w) = P_{WP}(t,w) + P_{DR}(t), \forall t, \forall w
\]  

(6.4)

\[ P_{W.of}(wu,t) \geq 0, \forall wu, \forall t \]  

(6.5)

\[ \text{Profit}(w) + \xi - \eta(w) \leq 0, \forall w \]  

(6.6)

\[ \eta(w) \geq 0, \forall w \]  

(6.7)

\[ \text{Profit}(w) = \sum_{wu=1}^{N_{wu}} P_{WDA}(wu,t) \lambda^{DA}(t) - P_{DR}(t) \lambda^{DR}(t) \\
+ P_{imb}(t,w) \lambda_{imb}(t,w), \forall t, \forall w \]  

(6.8)

\[ P_{DR}(t) = C_{DR.T}(t) \sum_{s=1}^{N_s} \pi(s) \cdot P_{W}(t,s), \forall t \]  

(6.9)
where $P_{WDA}(wu,t), \lambda^{DA}(t) \forall t \in \arg \text{ Minimize}$ \{

\[
\text{MinusSW} = \sum_{wu} N_{wu} P_{WDA}(wu,t) \lambda^{WDA} (wu,t) + \sum_{gu} N_{gu} \sum_{b=1}^{N_{b}} P_{G}(gu,b,t) \lambda^{G} (gu,b,t)
\]
\[
+ \sum_{dru} N_{dru} P_{DR,DA}(dru,t) \lambda^{DR,DA} (dru,t) - \sum_{du} N_{du} \sum_{db=1}^{N_{db}} P_{D}(du,db,t) \lambda^{D} (du,db,t)
\]

Subject to

\[
\sum_{wu} N_{wu} P_{WDA}(wu,t) + \sum_{gu} N_{gu} \sum_{b=1}^{N_{b}} P_{G}(gu,b,t) + \sum_{dru} N_{dru} P_{DR,DA}(dru,t)
\]
\[
= \sum_{du} N_{du} \sum_{db=1}^{N_{db}} P_{D}(du,db,t) : \lambda^{DA}(t)
\]

\[
0 \leq P_{WDA}(wu,t) \leq P_{W,of}^{W}(wu,t) \quad : \tau^{Min}(wu,t), \tau^{Max}(wu,t), \forall wu
\]

\[
0 \leq P_{G}(gu,b,t) \leq P_{G,Max}^{G}(gu,b,t) \quad : \alpha^{Min}(gu,b,t), \alpha^{Max}(gu,b,t), \forall gu, \forall b
\]

\[
0 \leq P_{DR,DA}(dru,t) \leq P_{DR,DA,Max}^{D}(dru,t) \quad : \theta^{Min}(dru,t), \theta^{Max}(dru,t), \forall dru
\]

\[
0 \leq P_{D}(du,db,t) \leq P_{D,Max}^{D}(du,db,t) \quad : \phi^{Min}(du,db,t), \phi^{Max}(du,db,t), \forall du, \forall db
\]

\}

and $sp_{W}^{W}(t,s) \forall t \in \arg \text{ Minimize}$ \{

\[
\text{MinusDR R} = -\sum_{s=1}^{N_{s}} \pi(s) C_{D,R,T}(t) \times \left[ sp_{W}^{W}(t,s) \lambda^{DR} (t) + \sum_{c=1}^{N_{TC}} sp^{C}(c,t,s) \lambda^{C} (c,t,s) \right]
\]

Subject to

\[
sp_{W}^{W}(t,s) + \sum_{dru=1}^{N_{dru}} sp_{DR,DA}^{DR,DA}(dru,t) + \sum_{c=1}^{N_{TC}} sp^{C}(c,t,s) = 1 \quad : \gamma(t,s), \forall s
\]

\[
sp_{W}^{W}(t,s), sp_{DR,DA}^{DR,DA}(dru,t), sp^{C}(c,t,s) \geq 0 \quad : \mu_{W}^{W}(t,s), \mu_{DA}^{DA}(dru,t), \mu_{C}^{C}(c,t,s), \forall s, \forall c, \forall dru
\]

\}

100
The upper-level problem is provided in (6.3)-(6.9). The profit function of the wind power producer is indicated in (6.3). The first term of this function shows the revenue obtained from selling into the day-ahead market. $P_{WD1}^{DA}(wu, t)$ and $P_{DA}^{DA}(t)$ are decided in the day-ahead market clearing process, i.e. the lower-level problem 1 (Eqs. (6.10)-(6.15)). The second term indicates the cost of DR. The third term is the revenue achieved from the balancing market. Note that if the wind power producer has deficit generation, it has to buy its deviation from the balancing market and hence, this term is a cost for the producer. Finally, the last term illustrates CVaR which is weighted using the risk factor ($\rho$). A risk level ($\rho$) close to 0 means that the wind power producer is risk-neutral while larger risk levels model risk-averse producers. $\beta$ is the confidence level, which is 0.95. Equation (6.4) enforces the power balance for wind power production. Non-negativity of the wind power offer ($P_{WF}^{WOF}(wu, t)$) in the day-ahead market is represented in (6.5). Expressions (6.6) and (6.7) represent CVaR constraints [56], which are derived to linearize this risk measure. Note that Profit($w$) in (6.6) indicates the obtained profit for scenario $w$, as illustrated in (6.8). In (6.9), $P_{DR}^{DR}(t)$ is formulated as a function of the DR percentage ($sp^{W}(t, s)$) which the DR aggregator sells to the wind power producer. This DR share ($sp^{W}(t, s)$) is indeed a variable which is determined by the DR aggregator, i.e. lower-level problem 2 (Eqs. (6.16)-(6.18)).

The lower-level problem 1 is addressed in (6.10)-(6.15). This problem clears the day-ahead market. In order to make a canonical representation, minus social welfare (MinusSW) is used in (6.10). The first three terms of this function respectively provide the offers by the wind power producer, other generators and the DR aggregator. The last term is the demand offer. The energy balance of the day-ahead market is imposed in (6.11). Constraints (6.12)-(6.15) respectively enforce the upper and lower limits of power for the wind power producer, other generators, the DR aggregator and the demand. Dual variables for each constraint are indicated following a colon.

As mentioned earlier, the DR percentage procured by the wind power producer ($sp^{W}(t, s)$) is determined in the lower-level problem 2. This problem is addressed in (6.16)-(6.18). The DR aggregator’s objective function is shown in (6.16). Again, minus revenue (MinusDR_R) is used in the objective function to make it canonical. The first two terms respectively indicate the expected revenues from the wind power producer as well as other players which are interested in buying DR. The last term represents the revenue obtained from selling DR to the day-ahead market. Note that this term is the product of two variables, i.e. $sp^{DR,DA}(dru, t)$ and $\lambda^{DA}(t)$. However, since these variables are decided in the lower-level problem 1, this product is constant here and we can remove it from the objective function. Instead, a new constraint is added to the problem to relate the lower-level problems 1 and 2:
Chapter 6. Demand Response Application by Strategic Wind Power Producers

\[ P_{DR, DA}^{t}(dru, t) = C_{DR, T}^{t}(t)sp_{DR, DA}^{t}(dru, t) \]  

(6.19)

Constraint (6.17) imposes that total DR share percentage must be equal to 1. Finally, constraint (6.18) is used for variable declarations. Again, dual variables for each constraint are indicated following a colon.

It should be emphasized that the variables of the lower-level problem 1 are \( P_{WDA}^{wu, t} \), \( P_{G}^{gu, b, t} \), \( P_{DR, DA}^{dru, t} \), \( P_{D}^{du, db, t} \), plus all dual variables shown in (6.11)-(6.15).

In addition, the variables of the lower-level problem 2 include:

\[ \Delta_{LL2}^{t} = \{ sp_{W}^{t}(s), sp_{C}^{t}(c, t, s), \gamma^{t}(t, s), \mu_{W}^{t}(t, s), \mu_{C}^{t}(c, t, s) \} \]

Finally, the upper-level variables contain all variables of the lower-level problems 1 and 2 plus the following:

\[ \Delta_{UL}^{t} = \{ \lambda_{DR}^{t}, P_{imb}^{t}(w, w), \lambda_{W, of}^{t}(wu, t), P_{W, of}^{t}(wu, t) \} \]

6.4 Linear Formulation

The given bilevel programming includes nonlinearity. This section provides an equivalent single-level linear problem, which is easily solvable by commercially available software. The following procedure is applied to linearize the nonlinear terms.

First, the bilevel problem is transformed into a single-level MPEC. For this purpose, each lower-level problem is replaced by its first-order optimality conditions through the KKT conditions [139]. Note that this transformation is valid since the lower-level problems are continuous and linear and thus convex.

The Lagrangian function of each lower-level problem is differentiated with respect to the relevant variables to derive its KKT optimality conditions. In addition, the complementarity slackness conditions obtained from these KKT conditions are linearized using Fortuny-Amat approach [140]. Expressions (6.20)-(6.39) show the corresponding derivatives for the lower-level problem 1.

\[ \lambda_{W, of}^{t}(wu, t) - \lambda_{DA}^{t}(t) + \tau_{Max}^{t}(wu, t) - \tau_{Min}^{t}(wu, t) = 0, \forall wu, \forall t \]  

(6.20)

\[ \lambda_{G}^{t}(gu, b, t) - \lambda_{DA}^{t}(t) + \alpha_{Max}^{t}(gu, b, t) - \alpha_{Min}^{t}(gu, b, t) = 0, \forall gu, \forall b, \forall t \]  

(6.21)

\[ \lambda_{DR, DA}^{t}(dru, t) - \lambda_{DA}^{t}(t) + \theta_{Max}^{t}(dru, t) - \theta_{Min}^{t}(dru, t) = 0, \forall dru, \forall t \]  

(6.22)

\[ \lambda_{DA}^{t}(t) - \lambda_{D}^{t}(du, db, t) + \phi_{Max}^{t}(du, db, t) - \phi_{Min}^{t}(du, db, t) = 0, \forall du, \forall db, \forall t \]  

(6.23)

\[ 0 \leq \tau_{Max}^{t}(wu, t) \leq M_{\tau}^{t} \]  

(6.24)
\[0 \leq P_{W,of}^{WDA}(w_u, t) - P_{WDA}^{WDA}(w_u, t) \leq M_{\tau}^{Max}(1 - v_{W,\max}^{W}(w_u, t)), \forall w_u, \forall t\] (6.25)

\[0 \leq \tau^{Min}(w_u, t) \leq M_{\tau}^{Min}v_{W,\min}^{W}(w_u, t), \forall w_u, \forall t\] (6.26)

\[0 \leq P_{WDA}^{WDA}(w_u, t) \leq M_{\tau}^{Min}(1 - v_{W,\min}^{W}(w_u, t)), \forall w_u, \forall t\] (6.27)

\[0 \leq \alpha_{Max}^{Max}(g_u, b, t) \leq M_{\alpha}^{Max}v_{G,\max}^{G}(g_u, b, t), \forall g_u, \forall b, \forall t\] (6.28)

\[0 \leq P_{GMax}^{Max}(g_u, b, t) - P_{G}^{G}(g_u, b, t) \leq M_{\alpha}^{Max}(1 - v_{G,\max}^{G}(g_u, b, t)), \forall g_u, \forall b, \forall t\] (6.29)

\[0 \leq \alpha_{Min}^{Min}(g_u, b, t) \leq M_{\alpha}^{Min}v_{W,\min}^{W}(g_u, b, t), \forall g_u, \forall b, \forall t\] (6.30)

\[0 \leq P_{G}(g_u, b, t) \leq M_{\alpha}^{Min}(1 - v_{W,\min}^{W}(g_u, b, t)), \forall g_u, \forall b, \forall t\] (6.31)

\[0 \leq \theta_{Max}^{Max}(d_r, u, t) \leq M_{\theta}^{Max}v_{DR,\max}^{DR,\max}(d_r, u, t), \forall d_r, \forall t\] (6.32)

\[0 \leq P_{DRMax}^{Max}(d_r, u, t) - P_{DR,DA}^{DR,DA}(d_r, u, t) \leq M_{\theta}^{Max}(1 - v_{DR,\max}^{DR,\max}(d_r, u, t)), \forall d_r, \forall t\] (6.33)

\[0 \leq \theta_{Min}^{Min}(d_r, u, t) \leq M_{\theta}^{Min}v_{DR,\min}^{DR,\min}(d_r, u, t), \forall d_r, \forall t\] (6.34)

\[0 \leq P_{DR,DA}^{DR,DA}(d_r, u, t) \leq M_{\theta}^{Min}(1 - v_{DR,\min}^{DR,\min}(d_r, u, t)), \forall d_r, \forall t\] (6.35)

\[0 \leq \phi_{Max}^{Max}(d_u, d_b, t) \leq M_{\phi}^{Max}v_{DR,\max}^{DR,\max}(d_u, d_b, t), \forall d_u, \forall d_b, \forall t\] (6.36)

\[0 \leq P_{DRMax}^{Max}(d_u, d_b, t) - P_{D}^{D}(d_u, d_b, t) \leq M_{\phi}^{Max}(1 - v_{DR,\max}^{DR,\max}(d_u, d_b, t)), \forall d_u, \forall d_b, \forall t\] (6.37)

\[0 \leq \phi_{Min}^{Min}(d_u, d_b, t) \leq M_{\phi}^{Min}v_{DR,\min}^{DR,\min}(d_u, d_b, t), \forall d_u, \forall d_b, \forall t\] (6.38)

\[0 \leq P_{D}^{D}(d_u, d_b, t) \leq M_{\phi}^{Min}(1 - v_{DR,\min}^{DR,\min}(d_u, d_b, t)), \forall d_u, \forall d_b, \forall t\] (6.39)

The KKT conditions of the lower-level problem 2 are shown in (6.40)-(6.45):

\[-\sum_{s=1}^{N_t} \pi(s)C_{DR}^{DR,T}(t) \lambda_{DR}^{DR}(t) - \gamma(t, s) - \mu_{W}^{W}(t, s) = 0, \forall s, t\] (6.40)

\[-\pi(s)C_{C}^{DR,T}(t) \lambda_{C}^{C}(c, t, s) - \gamma(t, s) - \mu_{C}^{C}(c, t, s) = 0, \forall c, \forall s, \forall t\] (6.41)

\[0 \leq sp_{W}^{W}(t, s) \leq M_{sp}^{W}v_{W}^{W}(t, s), \forall s, \forall t\] (6.42)

\[0 \leq sp_{C}^{C}(c, t, s) \leq M_{sp}^{C}v_{C}^{C}(c, t, s), \forall c, \forall s, \forall t\] (6.43)

\[0 \leq \mu_{W}^{W}(t, s) \leq M_{\mu}^{W}(1 - v_{W}^{W}(t, s)), \forall s, \forall t\] (6.44)

\[0 \leq \mu_{C}^{C}(c, t, s) \leq M_{\mu}^{C}(1 - v_{C}^{C}(c, t, s)), \forall c, \forall s, \forall t\] (6.45)

Note that \(M(. )\) parameters in all the above equations are sufficiently large constants and \(v( . )\) variables are binary variables.

103
The next step is to linearize the products of $P_{WDA}(wu,t) \times \lambda_{DA}(t)$ as well as $P_{DR}(t) \times \lambda_{DR}(t)$ in (6.3). The strong duality theorem is used to extract the linear formulation of these products. According to the strong duality theorem, the values of primal objective function and the dual function must be equal at the optimal solution [139].

**Lower-level problem 1:** The primal problem ($MinusSW$ from Eq. (6.10)) is equal to its dual (right hand side) as follows.

$$MinusSW = - \sum_{wu=1}^{N_{wu}} P_{W,of}^{W}(wu,t) \cdot \tau_{Max}(wu,t)$$

$$- N_{wu} \sum_{b=1}^{N_{b}} P_{GMax}^{W}(gu,b,t) \cdot \alpha_{Max}^{W}(gu,b,t)$$

$$\sum_{wu=1}^{N_{wu}} P_{WDA}(wu,t) \cdot \lambda_{DA}(t)$$

$$- N_{wu} \sum_{b=1}^{N_{b}} P_{W,of}^{W}(wu,t) \cdot \tau_{Max}(wu,t) , \forall t$$

(6.46)

Additionally, from slackness conditions we can derive:

$$\sum_{wu=1}^{N_{wu}} P_{WDA}(wu,t) \cdot \lambda_{DA}(t) = - N_{wu} \sum_{wu=1}^{N_{wu}} P_{W,of}^{W}(wu,t) \cdot \tau_{Max}(wu,t) , \forall t$$

(6.47)

Thus, substituting the above term in the primal problem ($MinusSW$) and simplifying it, the linear form of the product of $P_{WDA}(dru,t) \times \lambda_{DA}(t)$ is given as:

$$\sum_{wu=WU} P_{WDA}(wu,t) \cdot \lambda_{DA}(t) =$$

$$- \sum_{wu=WU}^{N_{wu}} P_{WDA}(wu,t) \cdot \lambda_{DA}(t)$$

$$- N_{wu} \sum_{b=1}^{N_{b}} P_{GMax}^{W}(gu,b,t) \cdot \alpha_{Max}^{W}(gu,b,t)$$

$$\sum_{wu=WU}^{N_{wu}} P_{WDA}(wu,t) \cdot \lambda_{DA}(t)$$

$$- \sum_{wu=WU}^{N_{wu}} P_{W,of}^{W}(wu,t) \cdot \tau_{Max}(wu,t) , \forall t$$

(6.48)

**Lower-level problem 2:** Similarly, we have the primal problem ($MinusDR_R$ from Eq. (6.16)) equal to its dual (right hand side) as follows:
\[
N_s \sum_{s=1}^{N_s} \pi(s) \gamma(t,s) = - \sum_{s=1}^{N_s} \pi(s) C^{DR,T}(t, s) - \sum_{c=1}^{N_{TC}} sp^C(c,t,s, \lambda^{DR}(c,t,s)) + \lambda^{DR}(t), \forall s, \forall t
\]  

(6.49)

Given the above duality and also from Eq. (6.9), the term \( P^{DR}(t) \times \lambda^{DR}(t) \) is easily obtained as follows.

\[
P^{DR}(t)\lambda^{DR}(t) = - \sum_{s=1}^{N_s} \pi(s) \gamma(t,s) - \sum_{s=1}^{N_s} \pi(s) C^{DR,T}(t) \sum_{c=1}^{N_{TC}} sp^C(c,t,s, \lambda^{DR}(c,t,s)), \forall t
\]

(6.50)

Overall, the equivalent single-level linear problem is as:

Maximize

\[
\sum_{wu=1}^{N_w} P^{WDA}(wu,t) \lambda^{DA}(t) - P^{DR}(t) \lambda^{DR}(t) + \sum_{w=1}^{N_w} \pi(w)P^{Imb}(t,w) \lambda^{Imb}(t,w)
\]

\[
+ \rho \left( \xi - \frac{1}{1 - \beta} \sum_{w=1}^{N_w} \eta(w) \pi(w) \right), \forall t
\]

subject to

Constraints (6.4)-(6.9), (6.11)-(6.15), and (6.17)-(6.19);

Constraints (6.20)-(6.45).

The derived problem in (6.51) is a mixed-integer linear programming approach. Note that the linear equivalent of the product of \( P^{DR}(t) \) and \( \lambda^{DR}(t) \) as well as that of \( P^{WDA}(wu,t) \) and \( \lambda^{DA}(t) \) are respectively presented in (6.48) and (6.50). Constraints (6.4)-(6.9), (6.11)-(6.15) and (6.17)-(6.19) of the original problem are applied here. (6.20)-(6.45) are associated with the KKT optimality conditions and the linearized complementarity slackness conditions.

### 6.5 Case Study

#### 6.5.1 Data Preparation and Assumptions

The proposed offering strategy is assessed on a realistic case of the Nordic market [137]. Demand, generators and DR offers are depicted in Table 6.1. The offers for demand and generators are taken from the Nordic market at 12 am on the 23th of January 2012. Since the cost offers of individual generators as well as demand are not publicly available, this chapter uses the supply and demand curves of the aggregated generation and demand offers, which are represented in the market clearing price (MCP) model of the Nordic market for the relevant hour. However, DR offers are assumed since there is no DR data available. These offers are indeed chosen in such a way as to
be close to other generators’ offers. The assumption is reasonable since the DR aggregator needs to compete with other power plants to be able to sell its DR product in the market.

The upper-level scenarios are generated as follows. The wind power producer Hemmet located in Denmark is chosen [138]. The installed capacity is 27MW (Vestas Turbines). Wind speed scenarios are generated using the ARMA model where the available data in 2012 is used as input time series. Ten wind speed scenarios are generated. These scenarios are then transformed into power scenarios using the Vestas Wind Curve. Note that in order to make the wind power producer influential in the market, we consider a wind farm size 200 times that of the given farm, i.e. 5400MW capacity.

In addition, ten imbalance price scenarios are generated. For this purpose, the ARIMA method is used. A time series of the prices of the Nordic market in 2012 is used to generate price scenarios.

In the lower-level problem, the rival DR prices, i.e. the DR price given to the DR aggregator by other players interested in DR, are considered to be stochastic. Three players are taken into account. In addition, 3 scenarios are generated to represent the uncertainty of each rival competitor.

### Table 6.1. Offers by demand, generators and DR in the day-ahead market

<table>
<thead>
<tr>
<th>Demand Offer</th>
<th>Generators’ Offer</th>
<th>DR Aggregator Offer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Volume (MWh)</td>
<td>Price ($/MWh)</td>
<td>Volume (MWh)</td>
</tr>
<tr>
<td>33662.2</td>
<td>55</td>
<td>25000</td>
</tr>
<tr>
<td>17</td>
<td>49.5</td>
<td>2000</td>
</tr>
<tr>
<td>17</td>
<td>45</td>
<td>2500</td>
</tr>
<tr>
<td>19.9</td>
<td>39.9</td>
<td>700</td>
</tr>
<tr>
<td>115</td>
<td>39.2</td>
<td>1000</td>
</tr>
<tr>
<td>57.3</td>
<td>35.31</td>
<td>1800</td>
</tr>
<tr>
<td>48.8</td>
<td>35</td>
<td>3000</td>
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<td>34.2</td>
<td>1000</td>
</tr>
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<td>647</td>
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<td></td>
</tr>
<tr>
<td>12.2</td>
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</tr>
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<td>8.4</td>
<td>32.51</td>
<td></td>
</tr>
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<td>17.3</td>
<td>32.3</td>
<td></td>
</tr>
<tr>
<td>44.1</td>
<td>32</td>
<td></td>
</tr>
<tr>
<td>24.7</td>
<td>31.6</td>
<td></td>
</tr>
<tr>
<td>52.1</td>
<td>31.5</td>
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<tr>
<td>165.1</td>
<td>31.4</td>
<td></td>
</tr>
<tr>
<td>329.3</td>
<td>30</td>
<td></td>
</tr>
</tbody>
</table>
6.5.2 Numerical Results

The proposed problem is solved for two risk levels using CPLEX 11.1.1 under GAMS [131].

Day-ahead market clearing prices for two risk-levels are shown in Table 6.2. Note that these prices are cleared as a result of exercising market power (strategic behaviour) by the wind power producer. While the risk-neutral producer fixes the price at $30/MWh, the risk-averse producer tends to increase the price to $31/MWh. This is sensible since the risk-neutral producer prefers to have a higher sale share in the day-ahead market and therefore keeps the price as low as possible to be successful in this market. On the other hand, the risk-averse producer is interested in selling more energy in the balancing market, where it has a better forecast of its production. Consequently, it increases the day-ahead price to compensate possible fluctuation (losses) in the balancing market.

| 𝜌=0 | 30 |
| 𝜌=10 | 31 |

Table 6.2. Day-ahead market clearing price

Table 6.3 provides the energy sold to the day-ahead market by the wind power producer (WPP), generation companies (GENCOs) and the DR aggregator. An interesting result is that as the risk level increases, the wind producer significantly decreases its participation in the day-ahead market. This indeed proves the discussion mentioned above. As a result of this declining trend and also because of the increased day-ahead price in risk level 10 (See Table 6.2), the shares of other generators as well as the DR aggregator grow. Note that the total demand served in both risk levels is identical. Indeed, the last demand offer, i.e. (329.3MWh, $30/MWh) is not approved in the day-ahead market in both risk levels.

Table 6.3. Energy Volume sold to the DA market by the WPP, GENCOs and the DR Aggregator (MWh)

| 𝜌=0 | WPP | GENCOs | DR Aggregator | Total |
| 𝜌=10 | 4643 | 30200 | 150 | 34993 |
| 𝜌=10 | 3493 | 31200 | 300 | 34993 |

Figure 6.2 displays the energy volume traded by the wind power producer in the balancing market. The wind power producer in risk level zero has to buy around 370MWh from the balancing market to compensate its overbid in the day-ahead market. Actually, the expected production of the wind power producer is around 4,280MWh while its power sold in the day-ahead market is
4.643MWh. On the other hand, the significant sale share of the risk-averse wind power producer ($\rho=10$) in the balancing market is obvious here.

The DR volume that the aggregator sells to each DR purchaser is depicted in Figure 6.3. The risk-neutral wind power producer has no DR procurement from the DR aggregator while the risk-averse producer purchases 500MWh. This is reasonable since the risk-averse producer tends to buy DR to compensate for its possible deviation in the real time. This tendency is confirmed in Table 6.4, where the risk-neutral wind power producer offers a DR price of $27.44/MWh while the risk-averse producer’s price given to the DR aggregator is $31/MWh. It is also obvious from Figure 6.3 that the DR aggregator sells more DR to the day-ahead market for $\rho = 10$. This is as a consequence of the higher day-ahead price in this risk level compared to the risk level equal to zero (See Table 6.2). Finally, as a result of the increment in the DR share of the wind power producer and the day-ahead market, that of other competitors declines in risk level 10.
6.5.3 Imbalance Price Sensitivity Analysis

This section analyses the impact of the imbalance price on the behaviour models of the strategic wind power producer. Three cases are considered. Case 1: the imbalance price is 95% of the original price used in the main study; Case 2: the outcomes of the main study; Case 3: the original imbalance price is increased by 5%.

The day-ahead market clearing price is delivered in Table 6.5. In addition, the wind power scheduled for different imbalance prices is provided in Figure 6.4. It can be seen that the day-ahead price for case 1 in risk level 10 decreases compared to the main case, i.e. Case 2. The strategic wind power producer bids in such a way as to reduce the market price and consequently sell a higher portion of its production in the day-ahead market (See Figure 6.4). This behaviour results since the imbalance price in Case 1 is low and therefore, the producer can easily compensate for its deviation from the day-ahead schedule in the balancing market at a low price. On the other hand, in case 3 where the expected imbalance price is high, both risk-neutral and risk-averse producers tend to increase the day-ahead market price. Thus, the risk-neutral can increase its profit in a higher day-ahead price. In addition, this producer reduces its share in the day-ahead market with the hope of selling energy in the balancing market at a higher price (Figure 6.4). However, the risk-averse producer does not take the deviation risk in case 3 with high imbalance prices. Therefore, it has no
participation in the day-ahead market with the aim of selling in the balancing market with the perfect knowledge of the market price as well as its power production.

| Table 6.5. Impact of the imbalance price on the DA market price ($/MWh) |
|-------------------|------------------|------------------|
|                   | 0.95% Imb. price | Imb. price       | 1.05% Imb. price |
| $\rho=0$         | 30               | 30               | 31               |
| $\rho=10$        | 30               | 31               | 32               |

Figure 6.4. Impact of imbalance price on wind power in the DA market

The participation of the wind power producer in the balancing market for various imbalance prices is shown in Table 6.6. The strategic behaviour of the producer is obvious, where in both risk levels it has to buy significant energy in case 1 while it has a substantial sales share in case 3.

| Table 6.6. Impact of the imbalance price on the wind power participation in the balancing market (MWh) |
|-------------------|------------------|------------------|
|                   | 0.95% Imb. price | Imb. price       | 1.05% Imb. price |
| $\rho=0$         | -696             | -366             | 1283             |
| $\rho=10$        | -696             | 1283             | 4726             |

In addition, the total demand cleared in different imbalance prices are shown in Figure 6.5. Imbalance prices affect the total demand scheduled in the day-ahead market, where higher imbalance prices lead to a falling trend in the demand served.
Finally, the impact of imbalance prices on the total DR procurement by the wind power producer is given in Table 6.7. The producer in both risk levels for case 1 is not willing to buy DR and thus, offers a low DR price to the aggregator (i.e. $27.44/MWh). On the other hand, both risk-neutral and risk-averse producers buy significant DR in high imbalance prices to cope with the risk of the balancing market (Case 3). Consequently, they offer $31/MWh to the DR aggregator and obtain 500 and 450 MW DR respectively.

| Table 6.7. Impact of the imbalance price on DR procurement by the wind power producer (MW, $/MWh) |
|-----------------|-----------------|-----------------|-----------------|
|                 | 0.95% Imb. price | Imb. price | 1.05% Imb. price |
| Volume | Price | Volume | Price | Volume | Price |
| $\rho=0$ | 0 | 27.44 | 0 | 27.4 | 500 | 31 |
| $\rho=10$ | 0 | 27.44 | 500 | 31 | 450 | 31 |

6.6 Summary

This chapter proposes a wind offering strategy through which a strategic wind power producer purchases demand response (DR) from a DR aggregator. The problem is formulated using a bilevel approach, where the upper-level represents the wind producer profit maximization while the lower-level problems respectively model the day-ahead market clearing process and the DR aggregator behaviour. The problem is then transformed into a linear approach through proper techniques.

The overall problem is solved using stochastic programming in which the risk is carried out using CVaR. It is assessed on a case of the Nordic Market. The main findings are as follows.
1. A strategic wind power producer affects the market by using its market power to fix the market price.

2. A risk-neutral producer plays strategically to increase its profit in the day-ahead market while the risk-averse producer uses its market power in such a way to compensate for possible deviations in the balancing market. In addition, the risk-averse producer tends to employ more DR for this purpose.

3. Imbalance prices have a significant impact on the behaviour of a strategic wind producer in the market as well as DR procurement.

Note that the proposed approach is applicable in electricity markets integrating substantial wind power production. Such markets with the mentioned regulatory framework exist in the real world, where Western Denmark, Germany and the state of South Australia are leaders. Note also that the market regulators are constantly updating the regulatory framework to overcome new issues. With regards to wind and renewable resources for instance, they first initiated new policies and incentives such as feed-in-tariff (FIT) schemes to grow these resources. However, as these resources became significant in some countries such as Denmark and Germany, they changed the rules and policies. For instance, Denmark has replaced FIT with a fixed premium payment in 2000, which is paid on top of earnings by wind farms in the market [101]. Furthermore, they may need to revise the rules and policies due to the significant increase of wind production which may bring several issues such as exercising market power. Therefore, the study of a price-maker wind producer may help the market regulator to better design rules and policies, which would result in increasing the competitiveness of the market [79].

The next chapter targets electricity retailers, as active players on the demand side, and presents the studies of the application of DR in their energy procurement problems.

### 6.7 Nomenclature

#### A) Indices

- **b**: Index for block of generators
- **c**: Index for customers
- **db**: Index for demand blocks
- **dru**: Index for DR units
- **du**: Index for demand units
- **gu**: Index for generator units
Chapter 6. Demand Response Application by Strategic Wind Power Producers

\(s\)  
Index for scenario in the lower-level problem

\(t\)  
Index for time

\(w\)  
Index for scenarios in the upper-level problem

\(wu\)  
Index for wind units

**B) Parameters**

\(C^{\text{DR,T}}(t)\)  
Total DR capacity

\(P^{\text{WP}}(t, w)\)  
Wind power production in scenario \(w\)

\(P^{\text{W,of}}(wu, t)\)  
Offered wind power in the DA market

\(P^{\text{DMax}}(du, db, t)\)  
Upper level of demand unit \(du\), block \(db\)

\(P^{\text{DRMax}}(dru, t)\)  
Upper level of DR unit \(dru\)

\(P^{\text{GMax}}(gu, b, t)\)  
Upper level of generation unit \(gu\), block \(gb\)

\(\lambda^{\text{D}}(du, db, t)\)  
Marginal utility of demand \(du\), block \(db\)

\(\lambda^{\text{C}}(c, t, s)\)  
DR price by competitor \(c\) in scenario \(s\)

\(\lambda^{\text{DR}}(t)\)  
DR price offered by the wind producer

\(\lambda^{\text{DR,DA}}(dru, t)\)  
Marginal cost of DR unit \(dru\)

\(\lambda^{\text{G}}(gu, b, t)\)  
Marginal cost of generator \(gu\), block \(b\)

\(\lambda^{\text{Imb}}(t, w)\)  
Imbalance price in scenario \(w\)

\(\lambda^{\text{W,of}}(wu, t)\)  
Offer price by the wind producer unit \(wu\)

\(\pi(w), \pi(s)\)  
Probability of scenario \(w\)/scenario \(s\)

**C) Variables**

\(P^{\text{D}}(du, db, t)\)  
Demand scheduled of unit \(du\), block \(db\)

\(P^{\text{DR}}(t)\)  
DR obtained by the wind power producer

\(P^{\text{DR,DA}}(dru, t)\)  
DR scheduled for aggregator unit \(dru\)

\(P^{\text{G}}(gu, b, t)\)  
Power scheduled for generator unit \(gu\), block \(b\)

\(P^{\text{Imb}}(t, w)\)  
Imbalance power by the wind producer

\(P^{\text{WDA}}(wu, t)\)  
Wind power scheduled in the DA market for wind unit \(wu\)
Chapter 6. Demand Response Application by Strategic Wind Power Producers

\[ s_{pC}^{c, t, s} \] DR share percentage of competitor \( c \) in scenario \( s \)

\[ s_{p^{DR,DA}}^{(dru, t)} \] DR share percentage of the DA market

\[ s_{pW}^{W(t, s)} \] DR share percentage of the wind producer

\( \lambda_{DA}^{(t)} \) DA market price

\( \xi, \eta^{(w)} \) Auxiliary variable for CVaR calculation

**D) Numbers and Sets**

- \( N_b \) Number of generator blocks
- \( N_{db} \) Number of demand blocks
- \( N_{dru} \) Number of DR units
- \( N_{du} \) Number of demand units
- \( N_{gu} \) Number of generator units
- \( N_s \) Number of scenarios in the lower-level problem
- \( N_{TC} \) Number of customers
- \( N_w \) Number of scenarios in the upper-level problem
- \( N_{wu} \) Number of wind power producer units
Chapter 7

Employing Demand Response by Electricity Retailers

7.1 Introduction

Electricity retailers are intermediary companies, which buy electricity from wholesale markets and sell to consumers. Electricity retailers participate in the pool market to procure part of their energy. Pool prices are volatile and in some cases see spikes. This imposes on retailers a significant level of risk. For instance, the real-time price for the state of Queensland, Australia during January 2011 is shown in Figure 7.1 [128]. As can be seen, while the price is mostly smooth, it faces huge spikes in some periods, which reaches just under $3,000/MWh.

As a resource to mitigate risk, electricity retailers can employ DR. A few studies in the literature address this concept. The authors in [86] use interruptible loads to alleviate the uncertainty of pool markets faced by a load serving entity. Two interruptible load contracts, pay-in-advance and pay-as-you-go, are evaluated in [92] as the supply to retailers. Self-production is also used in [93] to limit the risk of cost fluctuations in pool markets. Reference [94] uses interruptible loads as an energy resource of distribution companies. A short-term deterministic model is presented in [95] where distribution companies can use interruptible loads to bid in the market. Besides interruptible loads,

---

1 This chapter covers the following references:
real-time pricing and time-of-use are also offered by retailers to alter the electricity usage of consumers [96].

This chapter aims at demonstrating the application of DR in the energy procurement problem of electricity retailers, where the proposed DR framework in Chapter 3 is employed here. This framework allows retailers to decide how to procure various DR agreements from aggregators or large consumers in order to manage the risk of pool price fluctuations. Retailers are able to purchase DR through secure contracts (forward DR). They can also set DR option agreements (pool-order and spike-order options) which their exercising depends on pool market variations. Finally, they can rely on real-time DR (reward-based DR), its outcome being influenced by customers’ behaviour.

The effectiveness of the proposed DR framework is evaluated on an energy procurement problem, in which a retailer minimizes its energy cost while maintaining its desired risk level. It is assumed that the retailer employs DR in addition to forward contracts and pool markets. A stochastic programming approach is formulated, where pool prices and customer’s behaviour are uncertain. The risk is modelled by conditional value-at-risk (CVaR). The problem is analysed on a realistic case of the Queensland region within the Australian NEM.

The remaining of this chapter is organized as follows. DR contracts which are proposed to be used by electricity retailers are discussed in section 7.2. After that the wholesale resources, i.e. the pool market and forward contracts are explained. The problem formulations and case study come next. Sections 7.6 and 7.7 respectively represent the summary and nomenclature parts.
Chapter 7. Employing Demand Response by Electricity Retailers

7.2 Employing DR by Electricity Retailers

The proposed DR framework for retailers is shown in Figure 7.2. The retailer can set various DR contracts with DR aggregators or even consumers. Each contract is determined with a specific volume of DR, a certain price and the period in which the given contract is applied. Each contract has unique features which are discussed in this section.

Figure 7.2. The DR framework in the energy problem of a retailer

7.2.1 Pool-Order Option

A retailer may be interested in avoiding pool price fluctuations, even though they are small. In this way, it can arrange a pool-order option with a DR aggregator. Indeed, the pool-order option price is set in order to cover the possible cost imposed by normal pool price fluctuations. According to this contract the retailer has the right but not an obligation to purchase DR in real time. That is, the retailer signs this contract at the beginning of the decision time horizon. However, exercising the contract at the energy delivery time depends on whether it is profitable or not. If the contract is not exercised, the retailer has to pay a predetermined fee to the DR aggregator as the penalty of not exercising the contract.

The cost of pool-order options is mathematically formulated as:

\[
C(PO) = \sum_{t=1}^{T} \sum_{p_{po}=1}^{N_{po}} \left[ P_{po}(t) \lambda_{po}(t) \nu_{po}(t) d(t) + (1 - \nu_{po}(t)) f_{po}^{pen}(t) \right]
\]  
(7.1)
Chapter 7. Employing Demand Response by Electricity Retailers

Equation (7.1) represents the cost of the given pool-order option over the considered time horizon. It consists of two terms addressing the cost of practicing a pool-order option and the penalty of not exercising the agreed contract.

7.2.2 Spike-Order Option

A spike-order option agreement is proposed as a way to limit the huge cost faced by retailers during price spikes. This option is similar to the pool-order option, in which the retailer has the right but not an obligation to buy DR from a DR aggregator. The difference is that spike-order options are arranged to be used during periods with a possibility of price spikes. When retailers and DR aggregators set this contract they negotiate on a desired price, called a strike price. Considering the strike price, the retailer can decide whether or not to exercise the spike-order option at the delivery time. Note that similar to the pool-order option, the retailer has to pay a predetermined penalty if the contract is not exercised at the clearing time.

The cost of spike-order options is given in (7.2).

\[
C(SO) = \sum_{t=1}^{T} \sum_{s=1}^{N_{SO}} \left[ P_{SO}(t) \lambda_{SO}^{Str}(t) v_{SO}(t) d(t) + (1 - v_{SO}(t)) f_{SO}^{pen}(t) \right]
\]  

(7.2)

7.2.3 Forward (Fixed) DR

The retailer buys forward DR from aggregators for a future period. The price of typical forward contracts is usually determined in one of the following ways [129]:

- Over-the-Counter Market: prices are directly negotiated between the buyer and the seller of forward contracts.
- Exchange-Trade Market: this is a market where standardized contracts with given size and price are traded. The benefit of this type of trading is that prices are cleared and settled through a centralized clearing house.

Since the proposed DR provides a bilateral trading scheme between retailers and DR providers, the over-the-counter market is considered for forward DR agreements.

Forward DR contracts are offered in various blocks. The cost of forward DR is given as follows.

\[
C(FDR) = \sum_{t=1}^{T} \sum_{f=1}^{N_{FDR}} \sum_{b=1}^{N_{BDR}} P_{f,b}(t) \lambda_{f,b}^{DR}(t) d(t)
\]

(7.3)

\[
0 \leq P_{f,b}(t) \leq P_{f,b}^{DR,MAX}(t)
\]

(7.4)

Expressions (7.3) and (7.4) show the cost of forward contracts and the boundary size of each contract’s block, respectively.
7.2.4 Reward-Based DR

In addition to the mentioned bilateral DR contracts, a retailer may decide to implement reward-based DR with consumers. A reward-based DR function is modelled in a stepwise curve as shown in Figure 7.3. Based on this function, the volume of load reduction increases in a stepwise trend as the retailer offers higher rewards.

![Figure 7.3. The reward-based DR curve](image)

In addition, the uncertainty of customers’ behaviour is required to be taken into account. This is modelled using a scenario-based participation factor ($PF(w_t)$). This factor ranges between 0 and 1. Zero means that customers do not respond to the reward offered in the proposed reward-based DR. As this factor increases the participation rate grows. Finally, the participation factor equal to 1 indicates that the entire reward-based DR potential is attainable. Note that each participation scenario is identified with its own probability, where the summation of all probabilities is equal to one.

The overall reward-based DR is modelled as:

$$P_{DR}(t) = \sum_{w=1}^{N_w} \pi(w) \sum_{j=1}^{N_j} PF(w_t) \cdot \overline{P}_{DR}^{j}(t) \cdot v_{DR,j}(t)$$  \hspace{1cm} (7.5)

$$\overline{R}_{j-1}(t) \cdot v_{DR,j}(t) \leq R_{j-1}(t) \leq \overline{R}_{j-1}(t) \cdot v_{DR,j}(t)$$ \hspace{1cm} (7.6)

$$R_{DR}(t) = \sum_{j=1}^{N_j} R_{DR}^{j}(t)$$ \hspace{1cm} (7.7)

$$\sum_{j=1}^{N_j} v_{DR,j}(t) = 1$$ \hspace{1cm} (7.8)
Expressions (7.5)-(7.8) represent the total reduced demand by customers as a function of the reward offered by the retailer.

Taking into account the given DR equations (7.5)-(7.8), the expected cost of the reward-based DR over all scenarios is:

$$EC(RDR) = \sum_{w=1}^{N_{w}} \pi(w) \cdot \sum_{t=1}^{T} \left( \sum_{j=1}^{N_{j}} PF(w,t) \cdot P_{D}^{DR}(t) \cdot R_{D}^{DR}(t) \cdot d(t) \right)$$

(7.9)

### 7.3 Wholesale Market Suppliers

#### 7.3.1 Pool Market

The retailer is able to either buy energy from or sell to the pool market. Pool prices are uncertain and thus they are modelled using their plausible realizations. As a result, the expected cost of the pool market depends on price scenarios and is formulated as follows:

$$EC(P) = \sum_{w=1}^{N_{w}} \pi(w) \cdot \sum_{t=1}^{T} P_{P}(t,w) \cdot \lambda_{P}(t,w) \cdot d(t)$$

(7.10)

#### 7.3.2 Forward Contracts

A forward contract is usually set in different blocks, where each block is represented in a specific size and price. These blocks are provided in a stepwise manner where the price increases as the quantity of energy grows [16].

The cost of forward contracts is given in (7.11). Each forward agreement is also controlled by a minimum and maximum demand in (7.12).

$$C(F) = \sum_{t=1}^{T} \sum_{f=1}^{N_{FB}} \sum_{b=1}^{N_{FB}} P_{F}^{E}(t) \cdot \lambda_{F}^{E}(t) \cdot d(t)$$

(7.11)

$$0 \leq P_{F}^{E}(t) \leq P_{F}^{MAX}(t)$$

(7.12)

### 7.4 Problem Formulation

The proposed cost function (CF) consists of the cost terms as well as the risk measure (see 7.13). The first two terms respectively represent the costs of the pool market and forward contracts. The next four components address the costs of DR, where they are respectively the cost of reward-based
Chapter 7. Employing Demand Response by Electricity Retailers

DR, pool-order options, spike-order options and fixed (forward) DR contracts. The last term indicates the CVaR which is weighted using the risk factor. The risk level ($\rho = 0-\infty$) represents the trade-off between the expected cost and risk. A conservative retailer willing to minimize the risk chooses a large value of the risk factor. On the other hand, a risk-neutral retailer prefers lower costs and consequently selects a risk factor close to 0.

$$\text{MinCF} = \sum_{w=1}^{N_w} \pi(w), \sum_{t=1}^{T} P^P(t, w) \lambda^P(t, w) d(t) + \sum_{t=1}^{T} \sum_{f=1}^{N_F} \sum_{b=1}^{N_{FB}} P^F_{f,b}(t) \lambda^F_{f,b}(t) d(t)$$

$$+ \sum_{w=1}^{N_w} \pi(w), \sum_{t=1}^{T} \sum_{j=1}^{N_j} PF(w, t) \bar{P}^V_{j}^{DR}(t), R^V_{j}^{DR}(t) d(t)$$

$$+ \sum_{t=1}^{T} \sum_{po=1}^{N_{po}} \left[ P_{po}(t) \lambda_{po}(t), v_{po}(t) d(t) + (1 - v_{po}(t)) f_{pen}^{po}(t) \right]$$

$$+ \sum_{t=1}^{T} \sum_{so=1}^{N_{so}} \left[ P_{so}(t) \lambda_{so}(t), v_{so}(t) d(t) + (1 - v_{so}(t)) f_{pen}^{so}(t) \right]$$

$$+ \sum_{t=1}^{T} \sum_{b=1}^{N_{BDR}} \sum_{f=1}^{N_{DR}} \sum_{b=1}^{N_{BDR}} P_{f,b}(t) \lambda_{f,b}(t) d(t) + \rho \left( \zeta + \frac{1}{1 - \beta} \sum_{w=1}^{N_w} \eta(w) \pi(w) \right)$$

The cost function is subject to the following constraints:

- Expression (7.4) as the boundary limit of forward DR;
- Equations (7.5)-(7.8), indicating the reward-based DR model;
- The forward contracts enforcement (7.12);
- CVaR constraints:

$$\sum_{t=1}^{T} P^P(t, w) \lambda^P(t, w) d(t) + \sum_{t=1}^{T} \sum_{f=1}^{N_F} \sum_{b=1}^{N_{FB}} P^F_{f,b}(t) \lambda^F_{f,b}(t) d(t)$$

$$+ \sum_{t=1}^{T} \sum_{j=1}^{N_j} PF(w, t) \bar{P}^V_{j}^{DR}(t), R^V_{j}^{DR}(t) d(t)$$

$$+ \sum_{t=1}^{T} \sum_{po=1}^{N_{po}} \left[ P_{po}(t) \lambda_{po}(t), v_{po}(t) d(t) + (1 - v_{po}(t)) f_{pen}^{po}(t) \right]$$

$$+ \sum_{t=1}^{T} \sum_{so=1}^{N_{so}} \left[ P_{so}(t) \lambda_{so}(t), v_{so}(t) d(t) + (1 - v_{so}(t)) f_{pen}^{so}(t) \right]$$

$$+ \sum_{t=1}^{T} \sum_{b=1}^{N_{BDR}} \sum_{f=1}^{N_{DR}} \sum_{b=1}^{N_{BDR}} P_{f,b}(t) \lambda_{f,b}(t) d(t)$$

$$- \zeta - \eta(w) \leq 0; \forall w$$

$$\eta(w) \geq 0; \forall w$$

(7.15)
The power balance equation:

\[ p^{req}(t) = p^P(t,w) + \sum_{f=1}^{N_F} \sum_{b=1}^{N_{FB}} P_{f,b}(t) + \sum_{po=1}^{N_{po}} P_{po}(t) + \sum_{so=1}^{N_{so}} P_{so}(t) + \sum_{f=1}^{N_{EDR}} \sum_{b=1}^{N_{BDR}} p_{f,b}(t) + p_{DR}(t) \]

\[ (7.16) \]

### 7.5 Case Study

#### 7.5.1 Decision Time Horizon

The proposed problem is evaluated on the peak periods of summer and winter seasons in Queensland. The time horizon is divided into 32 periods, where each period corresponds to the peak times of one week. These periods consist of 12 weeks of January-March, 17 weeks of June-September and 3 weeks of December. Note that the peak period of summer days is from 11am to 9pm while those of winter days are from 6am to 10am and 4pm to 10pm. Note also that the values of demand and price for each period are taken by averaging their values in the peak times of Monday-Friday in each week.

A new factor, called the peak-to-average-ratio (PAR) is introduced in [23]. This ratio for daily load profiles is:

\[ PAR = \frac{\text{Max}\ L(t)}{\frac{1}{24} \sum_{t=1}^{24} L(t)} \]

\[ (7.17) \]

Where \( L(t) \) is the demand at hour \( t \). This concept is used here to evaluate the chosen peak periods.

First, the PAR is calculated for the annual load curve of Queensland in 2012. The peak demand in 2012 is 8,706MW and the average value is 5,826MW. Hence, the PAR is approximately equal to 1.49.

Then the PAR is calculated in a way that instead of the maximum demand in the numerator, the average of the peak demand in the chosen peak periods is used. This value over the considered 32 periods is around 6,654MW. Therefore, the value of the PAR is 1.14. It can be said that the PAR calculated based on the chosen periods (1.14) is around 24% lower than the annual PAR (1.49). Since the denominators in both calculated PARs are the same (both denominators are the average value of annual demand) it can be said that the chosen periods cover approximately the top 24% of the peak load in 2012.
Decisions on the given energy resources are made as follows. The retailer signs long-term derivatives, i.e. forward, pool-order options, spike-order options and forward DR at the beginning of the decision horizon. Throughout the time frame, decisions on 1) the execution of pool-order and spike-order options, 2) energy procurement from the pool market and 3) the energy obtained from reward-based DR, are taken.

### 7.5.2 Data Preparation and Assumptions

There are various retailers active in the Queensland region where the largest company provides around 50% of the total demand [144]. Thus the demand of the given retailer in this study is assumed to be equal to 50% of the Queensland demand for each period in 2012 [128]. Note that the demand of each period is calculated by averaging the peak periods of working days in the considered week.

The pool price is an uncertain input, which needs to be modelled stochastically. This is characterized using proper scenarios. An ARIMA model is applied here. ARIMA models are not very accurate for capturing the nonlinearity and volatility of price data. However, this study considers weekly prices, which obviously have a lower level of variability. Hence, the ARIMA model provides results with an acceptable accuracy for this case study. In order to prove this statement, the mean absolute percentage error (MAPE) index is calculated here, which is equal to 8.38%. Comparing this MAPE with other methods [145], the ARIMA outcome is reasonable.

A series of pool prices for Queensland from 2006-2012 is used to generate price scenarios [128]. This work uses the ARIMA model. A standard form of the ARIMA model is as follows.

\[
\left(1 - \sum_{i=1}^{P} \phi_i B^i\right) (1 - B)^d y_t = \left(1 - \sum_{i=1}^{Q} \theta_i B^i\right) \epsilon_t
\]  

(7.18)

where \( \phi_1, ..., \phi_P \) and \( \theta_1, ..., \theta_Q \) are \( P \) autoregressive and \( Q \) moving average parameters, respectively. \( B^i \) is the weight of each parameters and \( \epsilon_t \) stands for an uncorrelated normal stochastic process with mean zero and variance \( \sigma_t^2 \) and is referred to as white noise, innovation term, or error term. \( y_t \) is the stochastic process. \( B \) is the backshift operator and \( d \) represents the difference order.

The ARIMA model with its estimated parameters using Queensland prices from 2006-2012 is shown in (7.19). The first bracketed term indicates the autoregressive parameters. The second bracketed term represents the seasonality of the price data which is for each of 32 periods. The third bracketed term differentiates the process to make it stable in terms of the mean value. The logarithm function is also applied to stabilize the variance of prices. The right hand side of the equation states the moving average parameters. \( \epsilon(t) \) refers to the white noise or error term.
The standard deviation of the error is 0.586. Using the given ARIMA model, 150 sets of price scenarios are randomly generated for each period.

In addition, the behaviour of customers in reward-based DR is another source of uncertainty. For this purpose, five scenarios, ranging between 0 and 1 are randomly generated. These scenarios represent the participation factor in the reward-based cost function. Furthermore, five demand scenarios are generated to address the uncertainty of customers’ demand.

Forward contracts span each quarter of a year in the NEM. Therefore, three contracts (F1-F3) are considered here. F1 spans the periods of quarter 1, F2 covers the 17 weeks of winter and F3 relates to the December period. It is assumed that each forward contract involves six blocks, where each block is defined with a certain price and a maximum demand size. The forward prices of the Queensland region for each quarter of 2012 are used here [144]. Note that the maximum demand of each block in each period is 450MW.

Four pool-order and five spike-order options are taken into account. Each agreement involves a specific volume of demand and a negotiated price. The maximum demand quantities of each pool-order and spike-order option are 50 and 75MW respectively. The penalty of not exercising each option by the retailer is equal to 15% of the contract cost value. This penalty depends on the size of the contracted option and also the period in which the given option is set.

It is assumed that each forward DR contract is signed for a period of one month. Hence, eight forward DR agreements are provided covering eight given months of the planning horizon. Similar to forward contracts, each forward DR involves six blocks where the maximum contracted demand for each block is 75MW.

With regards to the reward-based DR, 21 successive steps are considered in the presented stepwise function.

The total potential of the given DR is around 30% of the entire demand. This potential is derived based on the trial DR potential carried out in Australia [146]. Figures 7.4-7.6 and Tables 7.1-7.2 illustrate the aforementioned input data.
Chapter 7. Employing Demand Response by Electricity Retailers

Figure 7.4. The expected demand required by the retailer

Figure 7.5. Pool-order option prices
Chapter 7. Employing Demand Response by Electricity Retailers

7.5.3 Numerical Results and Discussions

The given problem is mixed-integer linear programming, which is solved using CPLEX 11.1.1 under GAMS [131].

The expected cost versus standard deviation for various risk levels is shown in Figure 7.7. While a risk-neutral retailer (\(\rho=0\)) spends around $4.72 million, the energy cost of the most conservative retailer (\(\rho=5\)) is $5.3 million. On the other hand, the values of standard deviations for the risky and

![Figure 7.6. Spike-order option prices](image)

**Table 7.1. Forward prices ($/MWh)**

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**Table 7.2. Forward DR prices ($/MWh)**

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<td>33</td>
<td>35</td>
<td>37</td>
<td>39</td>
</tr>
<tr>
<td>FDR4</td>
<td>33</td>
<td>35</td>
<td>37</td>
<td>39</td>
<td>41</td>
<td>43</td>
</tr>
<tr>
<td>FDR5</td>
<td>45</td>
<td>47</td>
<td>49</td>
<td>51</td>
<td>53</td>
<td>55</td>
</tr>
<tr>
<td>FDR6</td>
<td>51</td>
<td>53</td>
<td>55</td>
<td>57</td>
<td>59</td>
<td>61</td>
</tr>
<tr>
<td>FDR7</td>
<td>56</td>
<td>58</td>
<td>60</td>
<td>62</td>
<td>64</td>
<td>66</td>
</tr>
<tr>
<td>FDR8</td>
<td>69</td>
<td>71</td>
<td>73</td>
<td>75</td>
<td>77</td>
<td>79</td>
</tr>
</tbody>
</table>
conservative retailers are approximately $2.08 million and $333,000 respectively. This means that the risk-neutral retailer obtains an 11% reduction in the expected cost compared to the conservative one. However, this retailer expects about 83% higher cost deviation. In other words, risk-neutral retailers are expected to buy their energy at lower costs while facing much higher cost fluctuations.

Figure 7.7. The expected cost vs. standard deviation

Figure 7.8 depicts the share of each resource in the total required energy by the retailer. The significant results are as follows.

- As the risk factor increases the share of DR resources grows. This is more obvious from $\rho=0$ to $\rho=0.2$, where the DR share increases more than twice. For larger risk levels by $\rho=5$ the DR contribution slightly increases to around 25%. This increment rate illustrates that the proposed DR agreements are more beneficial to conservative retailers than risky ones. This is reasonable since the given DR, particularly the long-term agreements are reliable resources.
- Since the pool market is a volatile resource, its energy share significantly drops once the risk factor rises. This trend is reversed for forward contracts.
Table 7.3 provides the percentage of each DR resource in the energy share of the retailer. As the retailer becomes more risk-averse, the share of all DR programs increases. This increment is significant in forward DR, where the DR share is around 4% for the risk-neutral retailer and around 14% for the most risk-averse one, i.e. 10% increment. The growth rate of pool-order and spike order options as well as reward-based DR is around 2%.

<table>
<thead>
<tr>
<th>$\rho$</th>
<th>Forward DR</th>
<th>Pool-Order Option</th>
<th>Spike-Order Option</th>
<th>Reward-based DR</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>3.96</td>
<td>3.02</td>
<td>2.26</td>
<td>0.61</td>
<td>9.86</td>
</tr>
<tr>
<td>0.2</td>
<td>12.55</td>
<td>3.63</td>
<td>2.55</td>
<td>1.40</td>
<td>20.13</td>
</tr>
<tr>
<td>0.5</td>
<td>13.58</td>
<td>4.38</td>
<td>3.68</td>
<td>1.87</td>
<td>23.51</td>
</tr>
<tr>
<td>0.7</td>
<td>13.58</td>
<td>4.71</td>
<td>3.82</td>
<td>1.98</td>
<td>24.09</td>
</tr>
<tr>
<td>1</td>
<td>13.58</td>
<td>4.71</td>
<td>3.82</td>
<td>2.05</td>
<td>24.16</td>
</tr>
<tr>
<td>5</td>
<td>13.58</td>
<td>4.81</td>
<td>4.17</td>
<td>2.20</td>
<td>24.76</td>
</tr>
</tbody>
</table>

Figures 7.9 and 7.10 provide the percentage of each resource in summer and winter seasons respectively. The main results interpreted from these Figures are listed below.

- Though the proportions of DR resources in summer and winter increase as the retailer becomes more risk-averse, this growth rate is higher in summer than winter. For instance, for $\rho=5$ DR programs account for around 26% of the summer share compared to 23% of winter energy. Additionally, it can be seen that more pool-order and spike-order options are exercised in summer than in winter.
• Conservative retailers prefer to sell energy to the pool market in winter. This is more obvious from \( \rho=0.2 \) to \( \rho=0.5 \), where the sold energy to the pool market becomes almost double.

Tables 7.4 and 7.5 respectively represent the periods in which pool-order (PO) and spike-order (SO) options are exercised.

From Table 7.4 it can be seen that a risk-neutral retailer only practices PO1 and PO2. For \( \rho=0.2 \), PO3 is also applied. For higher values of risk PO4 is also used in some periods. Similar to pool-order options, more spike-order options are utilized once the risk level increases (Table 7.5). The risk-neutral retailer uses only SO1. For \( \rho=0.2 \), SO2 is also applied in some periods. SO3 is exercised for the risk value of 0.5 and higher than that. SO4 is practiced for \( \rho=1 \) and \( \rho=5 \). Note that SO5 is not used in this case.

![Figure 7.9. The percentage of energy procured from each resource in summer](image)
Figure 7.10. The percentage of energy procured from each resource in winter

Table 7.4. Exercised periods of pool-order options

<table>
<thead>
<tr>
<th>$\rho$</th>
<th>PO1</th>
<th>PO2</th>
<th>PO3</th>
<th>PO4</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1--32</td>
<td>1--32</td>
<td>Not Employed (NE)</td>
<td>NE</td>
</tr>
<tr>
<td>0.2</td>
<td>1--32</td>
<td>1--32</td>
<td>5,7,10,21,24-32</td>
<td>NE</td>
</tr>
<tr>
<td>0.5</td>
<td>1--32</td>
<td>1--32</td>
<td>1-3,5,8,10,11,17-32</td>
<td>5,7,26,30</td>
</tr>
<tr>
<td>0.7</td>
<td>1--32</td>
<td>1--32</td>
<td>1-8,10,11,13,17-32</td>
<td>5-8,10,11,24,26,30</td>
</tr>
<tr>
<td>1</td>
<td>1--32</td>
<td>1--32</td>
<td>1-11,13,17-32</td>
<td>5-8,10,11,30,32</td>
</tr>
<tr>
<td>5</td>
<td>1--32</td>
<td>1--32</td>
<td>1-13,17-21,23-26,28-32</td>
<td>1-3,5-8,10,11,30,32</td>
</tr>
</tbody>
</table>

Table 7.5. Exercised periods of spike-order options

<table>
<thead>
<tr>
<th>$\rho$</th>
<th>SO1</th>
<th>SO2</th>
<th>SO3</th>
<th>SO4</th>
<th>SO5</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1--32</td>
<td>Not Employed (NE)</td>
<td>NE</td>
<td>NE</td>
<td>NE</td>
</tr>
<tr>
<td>0.2</td>
<td>1--32</td>
<td>5,7,10,11</td>
<td>NE</td>
<td>NE</td>
<td>NE</td>
</tr>
<tr>
<td>0.5</td>
<td>1--32</td>
<td>1-13,19,20,24,28,29</td>
<td>5,7</td>
<td>NE</td>
<td>NE</td>
</tr>
<tr>
<td>0.7</td>
<td>1--32</td>
<td>1-13,19,20,23,24,28,29</td>
<td>5,7,11</td>
<td>NE</td>
<td>NE</td>
</tr>
<tr>
<td>1</td>
<td>1--32</td>
<td>1-13,15,1719,20,23,24,29</td>
<td>5,7</td>
<td>NE</td>
<td>NE</td>
</tr>
<tr>
<td>5</td>
<td>1--32</td>
<td>1-15,17,19,20,24,29</td>
<td>5-8,10,11</td>
<td>7</td>
<td>NE</td>
</tr>
</tbody>
</table>
7.6 Summary

This chapter employs the proposed DR framework for electricity retailers. Various long-term and real-time DR contracts including pool-order options, spike-order options, forward DR and reward-based DR are used. These resources are applied as energy suppliers of a retailer in addition to the forward contracts and the pool market. A stochastic energy procurement problem is formulated where pool prices and customers’ enrolment in the reward-based DR are uncertain. The proposed scheme is evaluated on a realistic case of the Australian NEM for different risk levels. The main outcomes are as follows.

- The case study shows the feasibility of the proposed DR framework for retailers. The scheme allows retailers to procure their energy from various DR contracts.
- Depending on the risk level, retailers change their energy share from the proposed DR agreements. The risk-neutral retailer obtains around 10% of its energy from the given DR agreements. This share for the most conservative retailer (ρ=5) increases to around 25%. Forward DR agreements play a significant role in this increment with about 10% growth.
- The DR framework is employed in summer and winter. However, the usage rate in summer is higher than that in winter. This higher percentage is mostly due to the increasing usage of DR options.

The next chapter will study a market with high penetration of wind and PV power and proposes a co-optimization problem for ISOs in which they encourage DR aggregators to participate in reserve markets to alleviate renewable resources uncertainty.

7.7 Nomenclature

A) Indices

- $b$: Index for blocks in forward contracts
- $f$: Index for forward contracts
- $i$: Index for ARIMA parameters’ order
- $j$: Index for intervals in reward-based DR
- $po$: Index for pool-order options
- $so$: Index for spike-order options
- $t$: Index for time
- $w$: Index for scenarios
Chapter 7. Employing Demand Response by Electricity Retailers

B) Parameters

$B$ Backshift operator in ARIMA models

$B^i$ ARIMA parameters’ weight

$d$ The difference order in ARIMA models

$d(t)$ Duration of period $t$

$f_{po}^{pen}(t)$ Penalty of not exercising pool-order option $po$ during period $t$

$f_{so}^{pen}(t)$ Penalty of not exercising spike-order option $so$ during period $t$

$L(t)$ Load demand at hour $t$

$p_{DR,MAX}^{f,b}(t)$ Upper limit of demand in the $bth$ block of forward DR $f$ during period $t$

$p_{DR}^j(t)$ Demand of the $jth$ step of stepwise DR

$p_{MAX}^{f,b}(t)$ Upper limit of demand in the $bth$ block of forward contract $f$ during period $t$

$p_{po}(t)$ Power bought from pool-order $po$ in period $t$

$p_{so}(t)$ Power bought from spike-order $so$ in period $t$

$p_{req}(t,w)$ Required power by the retailer in period $t$

$pF(w,t)$ Scenario-based participation factor

$p_{DR}^{j}(t)$ Upper limit of the $jth$ interval of stepwise DR

$y_t$ Stochastic process in ARIMA models

$\beta$ Confidence level

$\rho$ Risk level

$\lambda_{po}(t)$ Price of pool-order option $po$ during period $t$

$\lambda_{f,b}^{DR}(t)$ Price of the $bth$ block of forward DR $f$ during period $t$

$\lambda_{f,b}^{F}(t)$ Price of the $bth$ block of forward $f$ during period $t$

$\lambda_{p}(t,w)$ Pool-price scenario $w$ during period $t$

$\lambda_{so}^{Str}(t)$ Strike price of spike-order $so$ during period $t$

$\varphi_i$ Autoregressive parameter $i$ in ARIMA models

$\theta_i$ Moving average parameter $i$ in ARIMA models
\( \pi(w) \) Probability of scenario \( w \)

**C) Variables**

\( p^{DR}(t) \) Power bought from reward-based DR in period \( t \)

\( p_{f,b}^{DR}(t) \) Power bought from the \( bth \) block of forward DR \( f \)

\( p_{f,b}^{F}(t) \) Power bought from the \( bth \) block of forward \( f \)

\( P^P(t,w) \) Power traded in the pool in period \( t \) and scenario \( w \)

\( R^{DR}(t) \) Reward offered by the retailer in period \( t \)

\( R_{j}^{DR}(t) \) Reward of the \( jth \) interval of stepwise DR

\( v_{DR,j}(t) \) Binary variable indicating if the \( jth \) interval of reward-based DR is applied in period \( t \)

\( v_{po}(t) \) Binary variable indicating if pool-order option \( po \) is exercised in period \( t \)

\( v_{so}(t) \) Binary variable indicating if spike-order option \( so \) is exercised in period \( t \)

\( \eta(w) \) Auxiliary variable for calculating CVaR

\( \zeta \) Auxiliary variable for calculating CVaR

**D) Numbers and Sets**

\( N_{BDR} \) Number of given blocks in forward DR

\( N_F \) Number of forward contracts

\( N_{FB} \) Number of forward contract’s blocks

\( N_{FDR} \) Number of forward DR contracts

\( N_J \) Number of intervals in the reward-based DR

\( N_{po} \) Number of pool-order options

\( N_{so} \) Number of spike-order options

\( N_{w} \) Number of scenarios

\( P \) Set for autoregressive parameters in ARIMA models

\( Q \) Set for moving average parameters in ARIMA models

\( T \) Set for time period
Chapter 8

Demand Response Application in an Electricity Market Integrating Wind and PV Resources

8.1 Introduction

High penetration of renewable resources brings some challenges to electricity markets. Wind power, usually in a large scale, is uncertain and non-dispatchable. The good thing however is that as wind penetration becomes significant, it is expected to be treated similar to conventional power plants. This observation is not valid for PV power, where it is usually on the demand side. Indeed, PV power imposes uncertainty to demand, which causes more difficulties in market dispatch carried out by ISOs.

Investigations are underway to resolve the above issues. A review of the literature indicates the majority of work is dedicated to wind related problems and their proposed solutions. Wind integration from an ISO point of view is modelled in some studies as in [102, 103, 108, 114]. The studies on PV are not as many as that of wind incorporation. A solar-powered micro-grid is studied in [147] where its pricing mechanism is proposed. A model for participating concentrating solar power in the market is proposed in [122], where the unit can use storage to increase its revenue. Economic impacts of solar power on the PJM electricity market are analysed in [123].

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1 This chapter covers the following reference:
There is no investigation which explicitly studies a system integrating both PV (small units) and wind power production while employing DR for easing their intermittency. This chapter studies an electricity market integrating wind and solar power. A single-period auction including energy and reserve markets is taken into account. In this context, wind power producers operate like conventional power plants, with the exception that they may only be capable of doing reserve down in the market. Additionally, plausible realizations of wind power production are taken into account to address wind power uncertainty. Load comprises three parts. The majority of the load is considered as an inelastic demand to be supplied in the energy market. In addition, PV power production is presented as a negative load deducted from the original load. PV power is variable, which is modelled as an uncertainty of the demand side. Finally, a limited specific portion of the load is considered to be elastic. A DR aggregator is proposed, which is responsible for this elastic load. The DR aggregator indeed enrols in the reserve market as a regulation up/down provider. The overall problem is formulated as a stochastic market dispatch problem carried out by an ISO. The problem is evaluated on a test case and also the IEEE RTS 24 bus system [103]. PV and wind power for this system are modelled from the Australian NEM realistic data.

The chapter is structured as follows. Section 8.2 discusses the proposed market clearing model from an ISO’s point of view. The case study is presented in the next section. The summary of the chapter and the nomenclature are explained in sections 8.4 and 8.5, respectively.

8.2 The Proposed Model

The proposed model studies a single-period market, which is more similar to the market dispatch presented in [103] than the security constrained unit commitment analysed in [148]. The model decides on the energy dispatch and reserve deployment. Indeed, energy decisions are made on the day prior to the market dispatch while those of the reserve market are cleared in real time. The following procedure is used in the proposed model.

Conventional power plants place their offer in the market while determining the maximum ramp up and ramp down that they can provide in the reserve market. The spinning reserve market is only modelled in this work. Nevertheless, non-spinning reserves can be included in the model with some modification. The cost associated with these power plants is given in (8.1). In addition, the size limit of the scheduled power of the generating unit \( g \) in the day-ahead market is enforced in (8.2). This limit for upward and downward regulation is posed in (8.3) and (8.4), respectively. Finally, constraint (8.5) ensures the total participation of the power plant does not exceed its maximum capacity.
Wind power producers are also able to offer their energy in the market. However, these producers can only make regulation down in the reserve market. This is the current practice for some semi-scheduled wind power producers in the Australian National Electricity Market [128]. In addition, similar to [103] the cost of downward regulation is assumed to be identical to the cost offer of the producer in the market. The cost function corresponding to the offer of wind power producer $\text{wp}$ is calculated as follows.

$$C_{wp}(P_{wp}^S + P_{wp,w}^r) \quad (8.6)$$

The wind spillage (downward regulation reserve by the wind power producer) is:

$$P_{wp,w}^r = P_{wp,w}^{total} - P_{wp}^S - P_{wp,w}^{spill} \quad (8.7)$$

Substituting (8.7) in (8.6), and since the term $C_{wp}P_{wp,w}^{total}$ is constant, the cost term of (8.6) can be simplified as follows.

$$-C_{wp}P_{wp,w}^{spill} \quad (8.8)$$

$$0 \leq P_{wp}^S \leq P_{wp}^{Expec} \quad (8.9)$$

$$0 \leq P_{wp,w}^{spill} \leq P_{wp}^S \quad (8.10)$$

Constraints (8.9) and (8.10) respectively impose the power scheduled in the day-ahead market and the spilled wind power in real time.

On the other hand, demand is considered to be mainly inelastic. Small-scale PV systems such as roof-top PV are taken into account as negative load. These systems have widely been used in Australia, particularly in the states of Queensland and South Australia. Some serious issues they have brought to the power system are voltage fluctuations, power quality problems and market
clearing issues. Of course, this chapter’s concern is on market related problems. Figure 8.1 indicates a typical weekly load profile of South Australia (SA) for a summer season (14-20 Jan 2013). It is obvious how PV production affects the load shape during the day. Additionally, the uncertainty of PV is noticeable, where for instance PV production in some periods such as the first day is significant while in others like the fourth day is small. This change and uncertainty may cause the shutdown of some power plants and in the worst case, wind power spillage. This is an obvious disadvantage since huge subsidies are spent in increasing wind power penetration while the market operator has to spill part of wind power as a result of PV production. For this reason, demand response (DR) is included as a solution. Therefore, DR aggregators are allowed to enrol in the reserve market. They can provide both types of reserves, i.e. upward and downward. Indeed, in the upward regulation they ask their customers to reduce their load while in the downward regulation they encourage consumers to consume more energy.

Overall the load model is formulated in (8.11).

\[
L_{lw}^{Net} = L_{lw}^{Orgl} - P_{lw}^{PV}
\]  

(8.11)

We assume that the part of the load which is inelastic has to be scheduled in the day-ahead market and it is derived as follows.

\[
L_i^S = L_i^{Orgl} - \sum_{w=1}^{N_w} \pi(w).P_{i,w}^{PV}
\]  

(8.12)

Thus, the cost term in the proposed market dispatch is indeed the cost of load shedding, shown in (8.13). The maximum load shedding is constrained in (8.14).
Finally, the cost related to the participation of DR in the reserve market is illustrated in (8.15). In addition, the sizes of regulation up and down are restricted in (8.16) and (8.17), respectively.

\[
C_{\text{dru}}^U r_{\text{dru},w}^U - C_{\text{dru}}^D r_{\text{dru},w}^D \leq \lambda_n \forall n : (\lambda_n) 
\]

subject to

\[
\sum_{g} P_{g} + \sum_{w} P_{wp} - \sum_{l} L_{l} = \sum_{r} B_{nr}(\delta_{n}^0 - \delta_{r}^0) \forall n : (\lambda_n) 
\]

\[
+ \sum_{l} (P_{l}^{\text{total}} - P_{wp}^{S} - P_{wp}^{\text{spill}} - \sum_{l} (L_{l,w}^{\text{Net}} - L_{l,w}^{S} - L_{l,w}^{\text{Shed}})) \forall n, w 
\]

\[
B_{nr}(\delta_{n}^0 - \delta_{r}^0) \leq C_{nr}^{\text{Line}} \forall n, w 
\]

Constraints for generators: (8.2)-(8.5)

Constraints for wind power producers: (8.9)-(8.10)
Constraint for load shedding: (8.14)
Constraints for demand response: (8.16)-(8.17)

The objective function comprises the expected cost of conventional power plants in both energy and reserve markets, and the expected cost of demand response, wind spillage and load shedding, all in the reserve market. Constraint (8.19) represents the power balance in the day-ahead market dispatch at each node. Note that the network losses are disregarded here while the model considers a power flow. Constraint (8.20) indicates the power balance enforcement in the reserve market. Note that $M(g,n)$ in constraints (8.19) and (8.20) shows whether generator $g$ is connected to bus $n$. The same definition is also valid for other connections in these constraints.

Constraints (8.21) and (8.22) impose the line capacity limit. The remaining constraints were explained earlier. The overall problem is a stochastic mixed-integer programming approach. CPLEX 11.1.1 under GAMS [131] is used to solve this problem.

8.3 Case Study

8.3.1 Three Bus System

A three-bus system is considered to assess the proposed problem. The information of this system is as follows [103]. The data for conventional power plants and demand response is provided in Table 8.1. It is assumed that the cost of reserve by conventional power plants is identical to the cost of their power production [103]. In addition, the uncertainty of wind and PV power is represented by three scenarios each, overall 9 scenarios (Table 8.2). The capacity of each line is limited by 100MW while the line reactance is 0.13 p.u. Note that for the sake of simplicity, network losses are neglected here. The original load located at bus 3 is 200 MW with the assumed VOLL of $1000. In addition, we assume that the wind power producer places its offer price at zero. Moreover, the maximum wind offer in the market is restricted by the expected wind power scenarios in Table 8.2, i.e. 30.5MW. Finally, the amount of load to be scheduled in the day-ahead market is obtained from Eq. (8.12).
Table 8.1. Generator data

<table>
<thead>
<tr>
<th></th>
<th>Max Power (MW)</th>
<th>Offer Cost ($/MWh)</th>
<th>Upward Cost ($/MWh)</th>
<th>Downward Cost ($/MWh)</th>
<th>Max Upward Power (MW)</th>
<th>Max Downward Power (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>G1</td>
<td>100</td>
<td>20</td>
<td>20</td>
<td>20</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>G2</td>
<td>50</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td>G3</td>
<td>100</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
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<tr>
<td>DR</td>
<td>-</td>
<td>-</td>
<td>30</td>
<td>30</td>
<td>20</td>
<td>20</td>
</tr>
</tbody>
</table>

Table 8.2. Wind and PV power scenarios (MW)

<table>
<thead>
<tr>
<th>Scenario</th>
<th>w1</th>
<th>w2</th>
<th>w3</th>
<th>w4</th>
<th>w5</th>
<th>w6</th>
<th>w7</th>
<th>w8</th>
<th>w9</th>
</tr>
</thead>
<tbody>
<tr>
<td>PV</td>
<td>10</td>
<td>20</td>
<td>30</td>
<td>10</td>
<td>20</td>
<td>30</td>
<td>10</td>
<td>20</td>
<td>30</td>
</tr>
<tr>
<td>Wind</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>35</td>
<td>35</td>
<td>35</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>Probability of each scenario</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.167</td>
<td>0.167</td>
<td>0.167</td>
<td>0.067</td>
<td>0.067</td>
<td>0.067</td>
</tr>
</tbody>
</table>

Figure 8.2. Three bus system

The DR capacity (Table 8.1) as well as PV and wind power production in Table 8.2 is considered as the base case. Consequently, six distinct cases are determined according to the base case (see Table 8.3). Note that the values represented for each resource, i.e. DR, PV and wind, indicate the percentage of the base case. Note also that the maximum wind offer also changes accordingly. Finally, it should be emphasized that the uncertainty of PV and wind power increases as the level of their penetration grows in the given cases.
Table 8.3. Studied cases with various resources integration (%)

<table>
<thead>
<tr>
<th></th>
<th>DR</th>
<th>PV</th>
<th>Wind</th>
</tr>
</thead>
<tbody>
<tr>
<td>C0</td>
<td>C0-1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>C1</td>
<td>C1-1</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>C1-2</td>
<td>0</td>
<td>150</td>
</tr>
<tr>
<td></td>
<td>C1-3</td>
<td>0</td>
<td>200</td>
</tr>
<tr>
<td></td>
<td>C1-4</td>
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The cases provided in Table 8.3 are as follows:

- **C0**: the system integrates neither DR nor renewable energy resources.
- **C1**: the system only has PV and wind. While wind production is identical to the base case, the PV penetration increases up to three times the base PV production.
- **C2**: this case is similar to C1, but it includes DR as well.
- **C3**: this case simultaneously studies the high penetration of wind and PV production while no DR is modelled.
- **C4**: C3 is studied while DR is added to the system.
- **C5**: this case is similar to C4, but it models the impact of an increasing DR penetration level.

Figure 8.3 displays the cost of the system for different cases. The following observations are made from the cost trend. First, it is obvious that integrating wind and PV resources reduces the
cost of the system (C0 vs. C1). In addition, introducing a higher penetration level of PV in the demand side leads to a decreasing cost of the system (See C1). This reduction is even higher with the application of demand response along with using PV (C2). One interesting result is that increasing the level of both wind and PV production is costly for the system (C3). In the worst case, the cost of the system in comparison with the base case increases by around 40% when the wind and PV penetration is three times more than the base case. This cost is alleviated when DR is used in the system (See C4). However, there is still an increasing trend for the system cost with regards to high levels of PV and wind production. This issue could be resolved when the DR capacity increases (C5). The reasons behind all changing trends are discussed in the following by giving more results.

![Figure 8.3. The cost of the system for various cases](image)

The amount of load shedding in cases C3, C4 and C5 are delivered in Figure 8.4. The load shedding occurs in scenarios 1 and 2 (w1 and w2) only. Note that the load is entirely supplied in other cases. The results indicate that load shedding in C3-2 is around 11 MW (only w1), while it is approximately 27 and 53 MW for C3-3 and C3-4, respectively. Applying the probability of these scenarios, i.e. 0.1, these values respectively come to 1.1, 2.7 and 5.3 MW load shedding in the mentioned cases. Indeed, these amounts of load shedding bring a high cost to the system as shown in Figure 8.3. Case 4 illustrates that employing DR by the ISO lessens the severity of load shedding. C4-2 has no load shedding while C4-3 and C4-4 still suffer from around 0.5 and 2 MW of the load that is not supplied. Consider that the DR potential in case 4 is limited by 20 MW and thus it cannot help the system to eliminate all the load shortage. This potential is doubled in case 5. Consequently, there is almost no load shedding in this case. In addition, the cost of the system significantly drops (Figure 8.3).
Table 8.4 compares the wind spillage in different cases for individual scenarios. No wind spillage is observed in the first four scenarios. These scenarios coincide with low and partly medium wind power scenarios in Table 8.2. The main findings from Table 8.4 are as follows. The increasing penetration of PV production in the demand side causes more wind spillage. Ultimately, in C1-5 where PV production is three times larger, wind is spilled 14.5 and 29.5 MW in scenarios 6 and 9, respectively. That means the overall spillage of around 4.4 MW in C1-5. The ISO can reduce this cut using DR (C2). However, there still exists wind spillage in scenario 9 of C2-4 and C2-5, where the PV penetration is considerably high. It is obvious that increasing wind and PV penetration simultaneously leads to higher wind spillage (C3). C3-4, where there is the highest wind and PV integration, a 21 MW wind cut results. This is just under five times greater than wind spillage in C1-5, where the wind penetration is one third. That is, the wind spillage does not follow a linear proportion to wind production. Similar to case 2, introducing DR eases the wind spillage and increasing its potential can even help more to this end (C2 & C5).

Table 8.5 illustrates how DR is able to facilitate both load shedding and wind spillage. Note that, regulations up and down are shown by ‘U’ and ‘D’, respectively. Note also that regulation up means that the DR aggregator exercises load reduction programs while in regulation down it encourages consumers to consume more energy. Consider scenarios 1 and 2 (w1 and w2) which coincide with the load shedding shown in Figure 8.4. The ISO accepts downward regulation from the DR aggregator in low penetration of PV. However, as the penetration of both PV and wind production grows, upward regulation is requested from the DR aggregator. In this way, the ISO is able to
manage load shedding by using DR (see Figure 8.4, C4 vs. C5). With regards to scenarios 5-9, where wind spillage occurs, it can be seen that the DR aggregator only provides downward regulation to compensate for this spillage.

<table>
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<th>w7</th>
<th>w8</th>
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Table 8.4. Wind spillage in different scenarios for the given cases (MW)
Table 8.5. Demand response in different scenarios for the given cases (MW)

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</table>

The wind power scheduled in the energy market is illustrated in Table 8.6. The ISO dispatches the maximum expected power of the wind power producer. This is sensible since the energy offer price of wind power is placed at zero.

Table 8.6. Wind power scheduled in the energy market (MW)

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<th>Case</th>
<th>Wind</th>
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</tr>
<tr>
<td>C3-4, C4-4, C5-4</td>
<td>91.5</td>
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</table>

The amount of power scheduled for conventional power plants is shown in Figure 8.5. The results obviously indicate a decreasing trend in the accepted offers of generators when the penetration of PV and wind production increases. This is reasonable since on one hand PV
integration reduces the net load while on the other hand, wind production is cheap and thus the ISO can reduce the system cost by using this resource. Another observation interpreted from Figure 8.5 is that DR slightly changes (small reduction) the scheduled power of conventional power plants.

![Bar chart showing scheduled power](image1)

**Figure 8.5.** The scheduled power for power plants in the day-ahead market

Since the main changes are in scenarios 1-2 and 5-9, Figure 8.6 and Table 8.7 study the upward and downward reserve for conventional power plants in these scenarios. Figure 8.6 shows the upward reserve in scenarios 1 and 2 for generators 2 and 3. It is obvious that increasing wind and PV production is followed by a higher upward reserve requirement from conventional power plants. This is sensible since wind power production in these scenarios is lower than the expected production. Thus, the ISO calls for conventional power plants to compensate for this deviation.

![Bar chart showing upward reserve](image2)

**Figure 8.6.** The upward reserve for conventional power plants
Table 8.7 represents the downward reserve deployed from generator 2 in scenarios 5-9 (w5-w9). Note that no downward reserve is procured from generator 3. The ISO does not require this reserve when there is no renewable production (C0). However, the integration of PV and wind urges the deployment of the downward reserve from generator 2. This is mainly because of the fluctuation between the values of the dispatched wind power and load scheduled in the day-ahead market and their real-time amounts. The results also illustrate that the need for downward reserve decreases as DR is introduced into the system (See C2 and C5). In addition, higher wind production results in the same need (C2 vs. C4).

<table>
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</tr>
<tr>
<td>C2-5</td>
<td>0</td>
<td>14.5</td>
<td>0</td>
<td>0</td>
<td>14.5</td>
</tr>
<tr>
<td>C3-1</td>
<td>6.75</td>
<td>20</td>
<td>14.25</td>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td>C3-2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>C3-3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>C3-4</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>C4-1</td>
<td>0</td>
<td>1.75</td>
<td>0</td>
<td>9.25</td>
<td>20</td>
</tr>
<tr>
<td>C4-2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>C4-3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>C4-4</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>C5-1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>C5-2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>C5-3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

8.3.2 A Case Study with the IEEE RTS System

The proposed problem is also studied for the IEEE 24-bus system [149] (Figure 8.7). The simulation is done for one period, i.e. 12pm. Two wind power producers are considered at buses 6
and 8. Each wind power producer is considered the size of three times the following wind farm. The wind farm Lake Bonney 2 in South Australia is chosen [135]. This wind farm is located at Mt Gambier AERO and its installed capacity is 159MW (53 Vestas 3MW Turbines). Wind speed scenarios are generated using the ARMA model where the summer season data from 2007-2012 is used as input time series. Twenty wind speed scenarios are generated for each site. The median wind power for this wind farm is 45 MW. Five PV units are considered at buses 5, 6, 8, 15, 18, 20. Ten PV power scenarios are considered where each scenario coincides with PV production in South Australia at 12pm. Overall 200 scenarios are generated with an identical probability. Note that PV production is rescaled based on the IEEE system to represent 10% of the total load at the relevant buses. DR aggregators are assumed to present their offers at buses 5, 6, 8, 15, 18. The cost offers of the DR aggregators are chosen in such a way that they are close to the power plants at or near their corresponding buses. Note also that the above PV and wind production is considered as the base case here. Four main cases are designed accordingly (Table 8.8).
Table 8.8. Cases considered for study on the IEEE RTS 24-bus system

<table>
<thead>
<tr>
<th>Case</th>
<th>DR</th>
<th>PV</th>
<th>Wind</th>
</tr>
</thead>
<tbody>
<tr>
<td>C0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>C1</td>
<td>C1-1</td>
<td>0</td>
<td>200</td>
</tr>
<tr>
<td></td>
<td>C1-2</td>
<td>0</td>
<td>300</td>
</tr>
<tr>
<td>C2</td>
<td>C2-1</td>
<td>100</td>
<td>200</td>
</tr>
<tr>
<td></td>
<td>C2-2</td>
<td>100</td>
<td>300</td>
</tr>
<tr>
<td>C3</td>
<td>C3-1</td>
<td>200</td>
<td>300</td>
</tr>
</tbody>
</table>

The cost of the system for various cases is depicted in Figure 8.8. The declining trend with respect to the higher integration of wind and PV power as well as the DR capacity confirms the results obtained from the 3-bus test case in Figure 8.3. Note that the system has no load shedding in the studied cases and thus it is not faced with the cost spikes shown in the previous section.

![Figure 8.8. The cost of the IEEE 24-bus system](image)

Power spillages for wind power producers 1 and 2 (WP1 & WP2) are provided in Table 8.9. The wind power spilled from the WP1 is significant while that of WP2 is low. In addition, it is obvious that integrating more PV leads to a higher level of wind spillage. This clearly shows the impact of PV and its production uncertainty on wind spillage in the market (Consider that there is no PV at WP2’s bus). Another observation is the impact of DR on the wind spillage. The results here also confirm the findings of the 3-bus case studied earlier.
Finally, the demand response deployed in the reserve market is displayed in Table 8.10. The results summarize the overall scenarios. Indeed, there are some scenarios in which upward reserve is required while for others DR is called for downward reserve. In addition, it is obvious that DR is mostly required to provide downward regulations at the buses which integrate wind power (dru2 and dru3). This is more apparent for dru3, where it provides downward reserve only.

### Table 8.10. DR deployed in the reserve market for the IEEE RTS 24-bus system

<table>
<thead>
<tr>
<th>Reserve</th>
<th>dru1</th>
<th>dru2</th>
<th>dru3</th>
<th>dru4</th>
<th>dru5</th>
</tr>
</thead>
<tbody>
<tr>
<td>C2-1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Upward</td>
<td>4.8</td>
<td>7.1</td>
<td>0</td>
<td>0</td>
<td>7.1</td>
</tr>
<tr>
<td>Downward</td>
<td>13.5</td>
<td>12.5</td>
<td>20</td>
<td>19.7</td>
<td>1.4</td>
</tr>
<tr>
<td>C2-2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Upward</td>
<td>7.1</td>
<td>7.1</td>
<td>0</td>
<td>7.1</td>
<td>15.9</td>
</tr>
<tr>
<td>Downward</td>
<td>12.7</td>
<td>12.7</td>
<td>20</td>
<td>12.1</td>
<td>1.3</td>
</tr>
<tr>
<td>C3-1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Upward</td>
<td>13.3</td>
<td>15.3</td>
<td>0</td>
<td>11.4</td>
<td>35.7</td>
</tr>
<tr>
<td>Downward</td>
<td>12.9</td>
<td>24</td>
<td>40</td>
<td>24.7</td>
<td>0</td>
</tr>
</tbody>
</table>

### 8.4 Summary

This chapter presents a market model for an ISO, which integrates high wind and PV power. DR is considered as a solution to resolving the issue related to the high level of wind and PV production. A DR aggregator is modelled, which is able to participate in the reserve market. The problem is formulated in a stochastic cost minimization from the ISO’s point of view. Plausible realizations of wind and PV power production are applied to represent their uncertainty. The proposed method is solved in a test case and also the IEEE 24-bus system using CPLEX 11.1.1 under GAMS. The main findings are as follows.

- Integrating wind and PV production reduces the cost of the system. However, higher levels of penetration may pose a high cost to the system. This is mainly due to the fluctuation of renewable resources, which causes load shedding in some cases.
- Employing DR can reduce the cost of the system. In addition, it may lessen the severity of load shedding as a result of high renewable power penetration. Furthermore, DR is
able to encourage consumers to consume more energy and consequently reduce the wind spillage.

- Increasing DR capacity for the systems with significant levels of renewable energy resources has a major impact on controlling these resources fluctuations as well as reducing the cost of the system.

### 8.5 Nomenclature

#### A) Indices

- \(dru\): Index for DR units
- \(g\): Index for generator
- \(l\): Index for loads
- \(n, r\): Index for bus
- \(w\): Index for scenarios
- \(wp\): Index for wind producers

#### B) Parameters

- \(B_{nr}\): Susceptance of line \(nr\)
- \(C^{D, DR}_{dru}\): Cost offer of demand response unit \(dru\) for downward regulation
- \(C^{U, DR}_{dru}\): Cost offer of demand response unit \(dru\) for upward regulation
- \(C_g\): Cost offer of generator \(g\)
- \(C^D_g\): Cost offer of generator \(g\) for downward regulation
- \(C^U_g\): Cost offer of generator \(g\) for upward regulation
- \(C_{Line}^{nr}\): Line \(nr\) capacity limit
- \(C_{wp}\): Cost offer of wind producer \(wp\)
- \(L_{Net}^{l,w}\): Net demand of load \(l\) in scenario \(w\)
- \(L_{Orgl}^{l}\): Original demand of load \(l\) without PV integration
- \(L_{l}^{s}\): Load scheduled in the day-ahead market
- \(p_g^{Max}\): Maximum power of generator \(g\)
- \(p_{PV}^{l,w}\): PV production at load point \(l\) in scenario \(w\)
Chapter 8. Demand Response Application in an Electricity Market Integrating Wind and PV Resources

\begin{align*}
P_{\text{Expec}}_{wp} & \quad \text{Forecast power of wind producer } wp \\
P_{\text{total}}_{wp,w} & \quad \text{Total power of wind producer } wp \text{ in scenario } w \\
R_{D,\text{DRMax}}_{dru} & \quad \text{Maximum downward reserve by demand response unit } dru \\
R_{U,\text{DRMax}}_{dru} & \quad \text{Maximum upward reserve by demand response unit } dru \\
R_{D,\text{Max}}_{g} & \quad \text{Maximum downward reserve by generator } g \\
R_{U,\text{Max}}_{g} & \quad \text{Maximum upward reserve by generator } g \\
V_{\text{oll}}_{l} & \quad \text{Value of lost load } l \\
\pi(w) & \quad \text{Probability of scenario } w \\
\end{align*}

C) Variables

\begin{align*}
L_{\text{shed}}_{l,w} & \quad \text{Load shedding for load } l \\
P_{g} & \quad \text{Power scheduled for generator } g \\
P_{\text{r}}_{wp,w} & \quad \text{Reserve power by wind producer } wp \\
P_{\text{s}}_{wp} & \quad \text{Power scheduled for wind producer } wp \\
P_{\text{spill}}_{wp,w} & \quad \text{Wind spillage of wind producer } wp \text{ in scenario } w \\
r_{D,\text{DR}}_{dru,w} & \quad \text{Downward reserve by demand response unit } dru \text{ in scenario } w \\
r_{U,\text{DR}}_{dru,w} & \quad \text{Upward reserve by demand response unit } dru \text{ in scenario } w \\
r_{D}^{g,\text{w}} & \quad \text{Downward reserve by generator } g \text{ in scenario } w \\
r_{U}^{g,\text{w}} & \quad \text{Upward reserve by generator } g \text{ in scenario } w \\
\lambda_{n} & \quad \text{Locational marginal price at node } n \\
\delta_{n}^{0} & \quad \text{Voltage angle at node } n \text{ in the day-ahead market dispatch} \\
\delta_{mw} & \quad \text{Voltage angle at node } n \text{ in the reserve market in scenario } w \\
\end{align*}

D) Numbers and Sets

\begin{align*}
N_{\text{dru}} & \quad \text{Number of DR units} \\
N_{g} & \quad \text{Number of generator} \\
\end{align*}
\( N_I \)  
Number of load

\( N_w \)  
Number of scenarios

\( N_{wp} \)  
Number of wind power producers
Chapter 9
Conclusions and Future Research

9.1 Summary

A demand response framework is presented in this thesis through which DR purchasers are able to bilaterally buy DR from a DR aggregator. The proposed DR framework includes various DR contracts, namely fixed DR, flexible DR and DR options. Each DR contract is described and formulated with unique features, which provides mutually attractive DR deals between a DR buyer and a DR aggregator.

The proposed DR framework is first applied to an offering strategy by wind power producers. Wind offering strategies for the Australian NEM and the Nordic market are proposed and formulated. These strategies allow a wind power producer to employ the proposed DR contracts in a two-step plan. The problem is further extended in which the DR aggregator behaviour is modelled in DR employment by wind power producers. In this way, a wind power producer has to compete with other players as well as electricity markets to obtain DR from the aggregator. Lastly, the application of DR by a strategic wind power producer, being able to exercise market power, is studied.

The proposed DR framework is also evaluated for retailers which are the main players in retail markets. A retailer is considered in such a way that it buys energy mainly from pool markets and forward contracts. In addition, the retailer is able to procure DR to lessen the risk of facing volatile pool prices. To this end, the retailer sets various DR contracts with a DR aggregator or directly
Chapter 9. Conclusions and Future Research

implements incentive-based DR programs with consumers. A reward-based DR is proposed for this purpose, where the uncertainty of consumers’ behaviour in responding to the reward offered by the retailer is modelled using a scenario-based participation factor.

Finally, the application of DR by an ISO is evaluated. A market with high penetration of wind power on the supply side and PV power on the demand side is modelled. The ISO seeks to balance the market at the real-time dispatch and hence, allows DR aggregators to participate in the reserve market in order to cope with the uncertainty of wind power and roof-top PV power.

The above problems are properly formulated using stochastic programming. All problems are rendered to linear programming, which is solvable using GAMS as commercially available software. The uncertain parameters such as wind power production, electricity market prices, consumers’ behaviour, rival DR purchasers’ actions and PV power are characterized using their plausible scenarios and the risk of these uncertain inputs are carried out using CVaR.

9.2 Main Findings and Contributions

The main conclusions of the proposed DR framework are outlined below.

1. The proposed DR framework helps a DR aggregator to become more active in the DR market. The aggregator is able to sell its DR product directly to the market or to DR purchasers through the proposed bilateral contracts.

2. In this DR framework the aggregator can provide a bidirectional energy flow between consumers and DR purchasers.

3. Time of Use programs depend on the elasticity of consumers while reward-based DR is mainly affected by the behaviour of consumers in responding to the offered incentives. Disregarding this uncertain behaviour may mislead the DR aggregator from its expected DR outcome in its reward-based DR strategy.

The main findings of the application of DR by wind power producers are as follows.

1. The proposed two-step plans for both the Australian and Nordic markets allow wind power producers to better offer in the market. In the Australian NEM, while the first-step decisions made on the preceding day are taken under uncertainty, step two allows the producer to take corrective actions once uncertain parameters are known. For the Nordic market, risk-neutral and risk-averse producers can determine the level of their participation in the day-ahead and balancing markets. While risk-neutral wind power
Chapter 9. Conclusions and Future Research

producers prefer to mostly sell in the day-ahead market, risk-averse producers have the higher share in a balancing market.

2. In the proposed plan, wind power producers arrange various DR contracts in step 1 (day ahead) and then manage them in step 2 (real time) to better cope with its uncertainty. They use fixed DR contracts to trade a certain amount of DR. In addition, they use flexible DR contracts, of which their usage distribution is manageable in real time. Furthermore, DR options give them a choice to set the contract and wait until real time to decide whether to exercise these contracts.

3. A wind power producer can buy DR during the peak price periods to lessen the risk of its power production and market price uncertainty. On the other hand, the producer is able to sell some portion of its energy through DR contracts during off-peak periods.

4. Modelling the DR aggregator behaviour makes DR trading more competitive since a wind power producer is required to compete with other players to offer reasonable DR prices to a DR aggregator.

5. A strategic wind power producer affects a market by using its market power to set market prices.

6. A risk-neutral strategic wind power producer tries to increase its profit in the day-ahead market while a risk-averse strategic producer uses its market power to compensate for possible deviations in the balancing market. In addition, the risk-averse producer tends to employ more DR for this purpose.

7. Imbalance prices have a significant impact on the behaviour of a strategic wind producer in the market as well as DR procurement.

The main outcomes in the application of DR by electricity retailers are given as follows.

1. The case study shows the feasibility of the proposed DR framework for retailers, where it allows retailers to procure their energy from various DR contracts and reward-based DR.

2. Depending on the risk level, retailers change their energy share from the proposed DR agreements. A risk-neutral retailer obtains a lower share of its energy from the given DR agreements. This share for a risk-averse retailer increases significantly, where fixed DR agreements play a significant role in this increment.
The main findings of employing DR by an ISO are listed below.

1. Integrating wind and PV production reduces the cost of the system. However, higher levels of penetration may pose a high cost to the system. This is mainly due to the fluctuation of renewable resources, which causes load shedding in some cases.
2. Employing DR can reduce the cost of the system. It is also useful for alleviating the severity of load shedding as a result of high renewable power penetration. Furthermore, a DR aggregator is able to encourage consumers to consume more energy and consequently reduce wind spillage.
3. Increasing DR capacity for systems with significant levels of renewable energy resources has a major impact on controlling these resources fluctuations as well as reducing the cost of the system.

9.3 Future Research

This thesis research can be further extended in the following areas:

1. The thesis focus is not on how a DR aggregator obtains DR from consumers. Modelling various DR programs to be implemented with consumers is a big area of research which can be studied as future work. For this purpose, the potential of each DR program, the periods in which each program is available, the consumers’ behaviour in detail, and various incentive and pricing schemes are required to be investigated.
2. The proposed wind offering strategy can be further extended in such a way that transmission networks are modelled. In this way, locational marginal prices are taken into account. In addition, a wind power producer needs to study how it can benefit from DR bought from DR aggregators in different locations than the one in which the wind power producer is located.
3. The ability of participating wind power producers in ancillary services markets needs additional research.
4. The behaviour of rival competitors in buying DR from a DR aggregator can be better modelled if there is realistic data available.
5. The ability of exercising market power is investigated in a market where there is only one player capable of this action. This study can be modified to cover oligopolistic markets, where more players behave strategically.
6. The problem of electricity retailers is extendable in such a way that consumers’ demand is explicitly modelled considering uncertainty. In addition, how a retailer attracts more consumers to sell energy to them may affect the problem. Furthermore, a mixed DR framework can be proposed, which allows a retailer to determine its DR share either directly from consumers or from a DR aggregator.

4. The problem of an ISO can be further investigated to consider a realistic system such as the South Australian system, where there is high penetration of wind and PV power. In addition, various DR products such as capacity and emergency DR can be defined to help the ISO better employ DR from DR aggregators. Furthermore, modelling a security-constrained unit commitment covering the whole 24 hours of the day of energy delivery makes our case stronger, where all technical aspects of power plants as well as load and DR are properly modelled.

7. The uncertain parameters throughout the thesis are mostly addressed using ARIMA models. This can be further enhanced by using more accurate forecasting models. This is particularly the case for wind power and price spike forecasts.

8. This thesis is focused on current electricity markets mostly at the transmission level. Future micro-grid markets are envisaged for distributing networks as the penetration of distributed generations and renewable sources increases. Further investigations are required to modify the presented concept to be applied to micro-grid markets, where stakeholders are residential customers, DR aggregators, retailers and micro-grid operators.
REFERENCES


162
References


References


References


References


References


References


References


Appendix A:

Papers Published and Submitted During This Research
Abstract—This paper deals with wind power offering strategies in day-ahead markets. A new plan is proposed in which a wind power producer participates in the day-ahead market while employing demand response (DR) to smooth its power variations. In this context, a new DR scheme is presented through which the wind power producer is able to achieve DR by establishing various DR agreements with DR aggregators. The proposed offering plan involves two stages: the first stage clears on the day-ahead market. The wind power producer decides on day-ahead offers as well as DR agreements with the aggregator. The second stage takes place on the balancing market. In a successive approach, the wind power producer determines its energy trading for each period until the whole day is covered. Additionally, proper DR agreements for each period are confirmed here. The proposed plan is formulated in a stochastic programming approach, where its validity is assessed on a case of the Nordic market.

Index Terms—Day-ahead market, demand response (DR) scheme, DR options, fixed DR, flexible DR, stochastic programming, two-stage wind offering plan.

I. INTRODUCTION

WIND energy has been a rapidly growing renewable resource in the past few years. This development is facilitated via various subsidies and supportive policies to achieve individual goals worldwide. The European Union and Australia have an identical target of achieving 20% of renewable energy by 2020. U.S. states have distinct goals. For instance, California is targeting 33% renewable by 2020.

The power production uncertainty is a significant challenge for wind power producers. Three main practical solutions are provided to cope with this issue: increasing the wind power forecasting accuracy, optimal wind trading strategies in short-term markets and a joint operation of wind power producers and easily controllable resources. This paper however focuses on the last two solutions.


With regards to joint operation strategies, [6] illustrates the coordination of wind and pumped-storage units. A joint planning and operation strategy of wind power producers and hydro power plants is provided in [7] and [8]. Facilitating wind power production with battery storage systems is described in [9]. Finally, the coordination of wind power producers and thermal plants is addressed in [10]. Demand response (DR) is another source, which can be used in a joint operation with wind power producers. However, relevant studies in literature mostly provide the coordination of DR and wind power producers to improve network and market operations [11]–[13].

This paper investigates a two-stage offering plan in which a wind power producer uses demand response (DR) as a joint operation resource. In the first stage, the wind power producer places its offer on the day-ahead market and simultaneously determines the contribution of DR agreements. These decisions are made while the following two points are taken into account: 1) wind power forecast for the coming day is not perfect and involves a significant level of uncertainty; 2) day-ahead prices and imbalance charges/payments are also uncertain parameters. A stochastic profit function is formulated where the decisions are taken based on the plausible realizations of the above stochastic parameters. To this end, for each uncertain parameter, a set of scenarios are generated by applying ARIMA models to the historical data. The risk is also carried out using conditional value-at-risk.

The second stage is dedicated to correction actions made on the balancing (regulating) market. A consecutive approach is proposed where the wind power producer settles its power trading in the balancing market for each period. At the same time, the wind power producer approves its required DR agreements with the DR aggregator. These decisions are taken while imbalance prices (charges/payments) and wind power are known for the current period but they are still uncertain for the following intervals. Again a stochastic profit function is formulated in this stage, which runs for each period. This process is repeated until all periods of the day are cleared.

In order to model DR in the proposed offering plan, a new scheme is presented through which a wind power producer can arrange various DR agreements with a DR aggregator. The wind power producer can set a fixed DR contract, which is traded in a
certain volume and price for a given period. In addition, a flexible DR is formulated, where it gives the wind power producer a chance to modify the usage pattern of the contracted DR during real-time usage. Furthermore, by adapting the financial option concept [14], new DR options are proposed here.

The proposed DR scheme is new as there is no such work in literature addressing a similar model. The majority of DR studies investigate the basic concept [15], [16], technical aspects [17] and DR formulations [18], [19]. Only authors in [20] and [21] study a mechanism through which DR is traded as a commodity. However, their method considers a pool-based DR exchange rather than bilateral contracts.

Overall, the contributions of the paper are as follows.
1) A two-stage offering plan in the day-ahead market is proposed in which wind power producers can benefit from DR in a joint operation.
2) A new DR scheme is proposed where DR can be traded as a public good between wind power producers and DR aggregators. For this purpose, various DR agreements with distinct features are proposed.

The rest of the paper is structured as follows. Section II discusses the given DR scheme with a detailed description of each DR agreement. The proposed plan is explained in Section III. Section IV provides a case study with numerical results. The last section concludes the paper.

II. COMPREHENSIVE DR SCHEME

The proposed DR scheme arranges mutually attractive deals between a wind power producer and a DR aggregator. It is assumed that the DR aggregator is willing to bilaterally trade DR with wind power producers. Indeed, the aggregator makes contracts with customers and implements technical DR programs to trade it with wind power producers (DR purchasers). A similar real case exists, where EnerNOC [22] plays an arbitrator role in a joint operation.

The proposed DR scheme is depicted in Fig. 1. As can be seen, DR is traded through three main contracts: DR options, fixed DR contracts and flexible DR agreements. Note that the double ended arrow indicates that the DR flow can be either from the aggregator to the wind producer or in the opposite direction. That is, the DR aggregator is also able to buy energy from the wind power producer through DR agreements, where in this situation it encourages customers to consume more energy. This usually happens during off-peak periods.

A. DR Options

A wind power producer can arrange DR options with DR aggregators. According to this contract the wind power producer has a right but not an obligation to purchase DR. This means that the wind power producer signs this contract at the beginning of the decision time horizon, i.e., Stage 1. However, exercising the contract at the energy delivery time (Stage 2) depends on whether it is profitable or not. Each DR option is determined with a specific offer including a certain volume and price for a given period. Thus, when the DR option is set in stage 1, the decision on whether signing this contract or not is made with perfect knowledge about the contract details. This decision is called here-and-now in stochastic programming, which is modeled as independent of scenarios [6]. In stage 2, the producer decides on exercising the DR options signed in stage 1. If the contract is executed in stage 2, the wind power producer pays its cost to the DR aggregator. Otherwise, the producer has to pay the predefined penalty. Note that this decision is also independent of scenarios since it is made while the wind power producer perfectly knows its production and the market price in the real-time dispatch.

Similar to financial options, two DR options are introduced. Type one is called European DR options (EDRO), which is set in a way that the DR agreement is exercised at the expiration time. The expiration time is defined when the contract is arranged. In type 2 however, the DR option can be exercised at any time before the expiration time (American DR option).

DR options in each stage are formulated as follows.

Stage 1: this stage indicates whether the DR option is signed or not. This is shown by the binary variable \( Sgn_{eo}(t) \) in the cost functions of European DR Option eo in (1a) and \( Sgn_{ao}(t) \) in American DR option ao in (1b):

\[
C_{es}^{EDRO,S1}(t) = P_{eo}(t) \times \lambda_{eo}(t) \times Sgn_{eo}(t) \times d_{e}
\forall e = 1, 2, \ldots, N_{eo}
\]

(1a)

\[
C_{as}^{ADRO,S1}(t) = P_{ao}(t) \times \lambda_{ao}(t) \times Sgn_{ao}(t) \times d_{a}
\forall a = 1, 2, \ldots, N_{ao}.
\]

(1b)

Subscripts eo and ao denote European and American DR options, respectively. \( P_{eo}(t) \) (\( P_{ao}(t) \)) and \( \lambda_{eo}(t) \) (\( \lambda_{ao}(t) \)) are the power traded in European DR option eo (American DR option ao) and its price during time t. \( d_{e} \) shows the duration of time period t (Note that since market dispatch intervals are identical, \( d_{e} \) is the same for all periods). Finally, \( N_{eo} \) (\( N_{ao} \)) represents the number of European DR options (American DR options).

Stage 2: this stage belongs to the delivery time in which it is decided that whether the signed DR option in stage 1 is exercised in stage 2 or not. The exercising status of the DR option is shown by a binary variable \( v_{eo}(t) \) in EDRO (2a) and \( v_{ao}(t) \) in ADRO (2b):

\[
C_{es}^{EDRO,S2}(t) = -Sgn_{eo}(t) \times \left\{ P_{eo}(t) \times \lambda_{eo}(t) \times v_{eo}(t) \times d_{e} + \right\}
\]

\[
\left\{ 1 - v_{eo}(t) \right\} \times f_{ro}(t)
\]

(2a)
∀\(t\in 1, 2, \ldots, N_{\text{ao}}\)
\[ C_{\text{ado}}^{S2}(t) = Sgn_{\text{ao}}(t) \times \left\{ \phi_{\text{ao}}(t) \times \lambda_{\text{ao}}(t) \times \nu_{\text{ao}}(t) \times d_1 + \left( 1 - \nu_{\text{ao}}(t) \right) \times f_{\text{pen}}^{\text{ao}}(t) \right\} \]

∀\(t\in 1, 2, \ldots, N_{\text{ao}}\).

\[ f_{\text{pen}}^{\text{ao}}(t) \text{ (} f_{\text{pen}}^{\text{ao}}(t) \text{)} \text{ is the penalty of not exercising the EDRO (ADRO) during time interval } t. \]

Note that American DR options can be exercised at any time before the expiration time. This constraint is provided in (3). This expression shows the period horizon \((t \in T_{\text{ao}})\) in which the American option \(\text{ao}\) can be exercised:

\[ \sum_{t \in T_{\text{ao}}} \nu_{\text{ao}}(t) \leq 1; \quad \forall\text{ao} = 1, 2, \ldots, N_{\text{ao}}. \]\n
### B. Fixed DR Contracts

A fixed contract is an agreement between a buyer and a seller of an asset to be traded at a future time [14]. Considering this concept, a fixed DR contract is proposed here, through which a wind power producer buys this contract from a DR aggregator. It is assumed that the wind power producer directly negotiates with the DR aggregator for a mutually attractive deal. Fixed DR contracts are offered in various blocks in which each block involves a certain amount of DR and price for a given period:

\[ C_{\text{f}}^{D}\text{R}^{F}(t) = F_{\text{f}}^{D}\text{R}(t) \times \lambda_{\text{f}}^{D}\text{R}(t) \times d_1 \]

\[ f = 1, \ldots, N_{\text{FDR}}, b = 1, \ldots, N_{\text{BDR}} \]

\[ P_{\text{f}}^{D}\text{R, MIN}(t) \leq P_{\text{f}}^{D}\text{R}(t) \leq P_{\text{f}}^{D}\text{R, MAX}(t). \]

Expressions (4) and (5) show the cost of the fixed DR and the margin size of each contract’s block, respectively. \(P_{\text{f}}^{D}\text{R}(t)\) and \(\lambda_{\text{f}}^{D}\text{R}(t)\) are the power and the price of the \(b\)th block of fixed DR \(f\). The number of contracts is given by \(N_{\text{FDR}}\) and the number of contract blocks is represented by \(N_{\text{BDR}}\).

### C. Flexible DR Agreement

Flexible DR agreements give the wind power producer a chance to better cope with the uncertainty of its power production as well as market price violations. When both parties (wind power producer and DR aggregator) set this contract (Stage 1), they negotiate the price and the duration of the agreement. However, during the delivery time (Stage 2) the wind power producer is flexible to manage the usage distribution of the contracted DR volume in the given period. That is, the wind power producer has the right to distribute the DR usage over the contract period to cope with its uncertainty.

The cost of the flexible DR agreement is provided in (6). \(P_{\text{f}}^{D}\text{R}(t)\) and \(\lambda_{\text{f}}^{D}\text{R}(t)\) are the power and the price of flexible DR \(f\), \(\phi_{\text{f}}^{D}\text{R}(t)\), \(U_{\text{f}}^{D}\text{R}(t)\) and \(P_{\text{f}}^{D}\text{R, MIN}(t)\) are a binary variable indicating whether the flexible DR \(f\) is used in period \(t\). \(N_{\text{f}}^{D}\text{R}(t)\) is the number of flexible DR contracts. The size of flexible DR is imposed in (7).

\[ C_{\text{f}}^{D}\text{R, MIN}(t) = P_{\text{f}}^{D}\text{R, MIN}(t) \times U_{\text{f}}^{D}\text{R}(t) \times d_1 \]

\[ f = 1, \ldots, N_{\text{f}}^{D}\text{R}(t), t = 1, \ldots, T_{\text{f}}^{D}\text{R}(t) \]

\[ \sum_{t = 1}^{T_{\text{f}}^{D}\text{R}(t)} P_{\text{f}}^{D}\text{R}(t) \times d_1 = E_{\text{f}}^{D}\text{R}(t) . \]

### III. PROPOSED TRADING PLAN

The proposed offering plan is applied on the Nordic market, which is a well-established day-ahead market. This market involves three floors, called the spot market, Elbas as an adjustment market, and the regulating market [1]. Elbas is not very active [1] and hence it is not modeled here.

The spot market closes at 12:00 pm the preceding day of the energy delivery. Then, offers and bids from players are stacked and the market price is derived. The revenue obtained from the day-ahead market is formulated in (9):

\[ R^{DA}(t, w) = P^{DA}(t) \times \phi^{DA}(t, w) \times d_1. \]

\(P^{DA}(t)\) is the offered power in the day-ahead market during period \(t\). \(\phi^{DA}(t, w)\) represents the price of the day-ahead market in scenario \(w \in \Omega\) during time period \(t\).

The regulating (balancing) market is used to balance between production and consumption. The balancing market can be either “short” or “long”. In the short state, there is lack of energy while the long market has excess production [8]. Note that long and short markets are respectively known as positive and negative system imbalances in most studies [3], and thereafter we use these terms in the paper. In positive systems, regulation down is activated and generators with excess (deficit) generation are paid (charged) at a positive price \(\phi^{imb, pos}\) (negative price \(\phi^{imb, neg}\)). On the other hand, in negative system imbalances, regulation up is applied and payments (charges) for excess (deficit) generation are settled at \(\phi^{imb, pos}\) (\(\phi^{imb, neg}\)). For each regulation type, the relationships of \(\phi^{imb, pos}\) and \(\phi^{imb, neg}\) with the day-ahead market price \(\phi^{DA}\) are given in [3] as follows:

\[
\begin{align*}
\Down & \quad \phi^{imb, pos} < \phi^{DA} < \phi^{imb, neg} \\
\Up & \quad \phi^{imb, pos} = 0.95 \times \phi^{DA} \quad \phi^{imb, neg} = 1.05 \times \phi^{DA}
\end{align*}
\]

An estimation of imbalance payments and charges for the Nordic is provided in [8]:

\[ \phi^{imb, pos} = 0.95 \times \phi^{DA} \]
\[ \phi^{imb, neg} = 1.05 \times \phi^{DA}. \]

This paper further extends the given model in a way that the uncertainty of the regulating market is taken into account:

\[ \phi^{imb, pos} = S_{pos}(w) \times \phi^{DA} \]
\[ \phi^{imb, neg} = S_{neg}(w) \times \phi^{DA} \]

where \(S_{pos}(w) \leq 1\) and \(S_{neg}(w) \geq 1\) are the scenario-based factors of positive and negative imbalance prices, respectively.
Depending on whether the wind power producer has excess or deficit production in the balancing market, it earns revenue or incurs cost. The revenue (payment) or cost (charge) of the balancing market is then formulated as follows [3]:

\[ R^{Inc}(t, w) = P^{pos}(t, w) \times S^{pos}(t, w) \times \lambda^{DA}(t, w) \times d_t - P^{neg}(t, w) \times S^{neg}(t, w) \times \lambda^{DA}(t, w) \times d_t \]  

where \( P^{pos}(t, w) \) and \( P^{neg}(t, w) \) are the positive and negative imbalance power volumes in scenario \( w \in \Omega \) and time period \( t \).

The proposed offering strategy is illustrated in Fig. 2. It is assumed that the wind power producer is a price-taker in the market. A further assumption is that the wind power producer is treated as similar to conventional power plants [23], where it is responsible for its bidding strategy and power production variation. Note that this producer acts as a balance responsible player in the Nordic market, where it is responsible for its imbalance charges/payments. In addition, similar to [8] this paper aims to determine the optimal offering quantities instead of presenting bidding curves which is investigated in [3].

A. Stage 1: Day-Ahead Clearing

This stage clears on the day-ahead market. The wind power producer decides on day-ahead offers for the entire next day. In addition, the volume of fixed DR contracts is negotiated. Furthermore, the wind power producer determines the periods in which European DR options are signed. Proper American DR options are also signed and the time horizon in which each one can be exercised is determined. Finally, the required flexible DR agreements are appointed.

The above decisions are made while wind power production as well as day-ahead and imbalance prices (charges/payments) are uncertain. A stochastic profit function is formulated in which the uncertain characteristics of these parameters are taken into account using a set of scenarios. In addition, the risk faced with this uncertainty is modeled through CVaR as an appropriate risk measure.

The profit function is given in (15). This function is calculated for the whole day \( t \rightarrow 1 \colon F^{PP} \). It consists of the following terms. The expected revenue obtained from selling power through the day-ahead market, the expected revenue/cost of the balancing market, the costs of all DR contracts and the weighted CVaR. Note that \( \pi(w) \) is the probability of scenario \( w \). \( \xi \) and \( \eta_{w} \) are auxiliary variables for calculating CVaR [3], and \( \beta \) is the confidence level, which is 0.95. Note also that the risk level \( \rho = (0 - \infty) \) represents the trade-off between the expected profit and the risk. A risk-averse wind power producer willing to minimize the risk chooses a large value of the risk. On the other hand, a risk-neutral wind power producer prefers higher profits and consequently selects a risk factor close to 0.

The profit function is subject to the following constraints. The size of fixed DR and flexible DR contracts are enforced by (16) and (17), respectively. Furthermore, the positive and negative imbalance offers are limited by (18) and (19) respectively. \( P^W(t, w) \) is wind power production in scenario \( w \) and time \( t \). \( P^{IncW} \) is the installed capacity of the wind power producer. The power balance is given in (20). In this equation, \( P^{Inc}(t, w) \) and \( P^{TDR}(t) \) represents the imbalance power and total DR volume, where they are represented in (21) and (22), respectively. Finally, expressions (23) and (24) represent CVaR constraints [3], which are derived to linearize this risk measure. Note that Profit/(w) in (23) indicates the obtained profit in scenario \( w \) [see (25)]:

Max \( \sum_{u \in \Omega} \pi(u) \times \sum_{t=1}^{FP} [R^{DA}(t, u) + R^{Inc}(t, w)] \)

subject to

\[ \sum_{u \in \Omega} \sum_{t=1}^{FP} C^{ADRO,S1}(t) - \sum_{t=1}^{FP} \sum_{u \in \Omega} \sum_{t=1}^{N_{DR}} C^{EDRO,S1}(t) \]

\[ \sum_{t=1}^{FP} \sum_{u \in \Omega} \sum_{t=1}^{N_{DR}} C^{FDR}(t) - \sum_{t=1}^{FP} \sum_{u \in \Omega} \sum_{t=1}^{N_{DR}} C^{TDR}(t) \]

\[ + \rho \times \left( \xi - \frac{1}{\beta} \sum_{u \in \Omega} \beta_{w} \times \eta_{w} \right) \]  

\[ \sum_{u \in \Omega} \sum_{t=1}^{FP} \sum_{u \in \Omega} \sum_{t=1}^{N_{DR}} P^{DR}(t) \leq P^{DR}(t) \leq P^{DR}(t) \]  

\[ \sum_{u \in \Omega} \sum_{t=1}^{FP} \sum_{u \in \Omega} \sum_{t=1}^{N_{DR}} P^{DR}(t) \leq P^{DR}(t) \leq P^{DR}(t) \]  

\[ 0 \leq P^{pos}(t, w) \leq P^{W}(t, w) + P^{TDR}(t) \]  

\[ 0 \leq P^{neg}(t, w) \leq P^{IncW} + P^{TDR}(t) \]  

\[ P^{DA}(t) + P^{Inc}(t, w) = P^{W}(t, w) + P^{TDR}(t) \]  

\[ P^{TDR}(t) = \sum_{f=1}^{N_{DR}} \sum_{b=1}^{N_{DR}} P^{DR}(t) \]  

\[ + \sum_{f=1}^{N_{DR}} P^{TDR}(t) \times U P^{TDR}(t) \]
B. Stage 2: Regulating (Balancing) Market

Stage 2 deals with balancing settlements and final DR approvals. This stage runs a successive approach, which is repeated until all periods are covered. For each period a profit function is formulated through which the following decisions are made. The wind power producer decides on its energy trading in the balancing market for the current period. At the same time the producer determines its optimal share of DR agreements for the relevant period. Indeed, each DR agreement that has been set in the previous stage is finalized here. The wind power producer decides on the optimal usage of flexible DR. The constraint used here is that the total flexible DR usage should not exceed the agreed volume in stage 1 [see (8)]. Furthermore, the wind power producer decides on exercising the signed DR options in stage 1. In this way, the producer considers that European DR options are exercised only at the expiration time, while American DR options can be used at any time before the deadline. Note that the volume of the contracted fixed DR is predetermined in stage 1 and cannot be changed in this stage.

The above decisions are taken while the day-ahead awards (offers) are known. In addition, the imbalance price and wind power production for the current period are known, but they are still uncertain for the following periods.

The profit function which is formulated for each period is shown in (26). It consists of three terms: the profit obtained from the current period \((t = CP)\) [see (27)], the expected profit over the following intervals until the final period \((t \rightarrow (CP + 1) : FP)\) [see (28)] and CVaR. Note that the main terms involve the (expected) revenue/cost of the balancing market as well as the costs of DR agreements. Note also that the binary variable \(v_{f,b}(t) \in \{0,1\}\) states whether the \(b\)th block of fixed DR \(f\) is set in stage 1. A similar variable is also used for the flexible DR status \((v_{flex}(t))\):

\[
P_F = \text{Prof}(t)_{|t=CP} + \text{EProf}(t)_{|t=CP+1} + \rho \cdot \text{CVaR} \quad (26)
\]

where

\[
\text{Prof}(t)_{|t=CP} = - R C_{\text{in,h}}(CP) - \sum_{a=1}^{N_{as}} C_{a}^{ADRO,S1}(CP) - \sum_{e=1}^{N_{eo}} C_{e}^{EDRO,S1}(CP) - \sum_{f=1}^{N_{fr}} \sum_{b=1}^{N_{br}} C_{f,b}^{FRN}(CP) \times v_{f,b}(CP) - \sum_{f=1}^{N_{flex}} C_{flex}^{FR}(CP) \times v_{flex}(CP) \quad (27)
\]

\[
\text{EProf}(t)_{|t=CP+1} = \sum_{w \in \Omega} \Pi(w) \times \sum_{t=CP+1}^{FP} [R C_{\text{in,h}}(t,w)] - \sum_{a=1}^{N_{as}} C_{a}^{ADRO,S1}(t) - \sum_{t=CP+1}^{FP} \sum_{e=1}^{N_{eo}} C_{e}^{EDRO,S1}(t) - \sum_{t=CP+1}^{FP} \sum_{f=1}^{N_{fr}} \sum_{b=1}^{N_{br}} C_{f,b}^{FRN}(t) \times v_{f,b}(t) - \sum_{t=CP+1}^{FP} \sum_{f=1}^{N_{flex}} C_{flex}^{FR}(t) \times v_{flex}(t) \quad (28)
\]

The profit function is subject to the following constraints.

- Constraints (17)–(25). Note that in these constraints, the day-ahead awards are known. In addition, only those DR agreements set in stage 1 are taken into account here.
- Flexible DR energy constraint:

\[
\sum_{t=0}^{CP-1} P_{flex}^{DR}(t) + \sum_{t=CP}^{FP} P_{flex}^{DR}(t) = F_{Ag}^{Ag} \quad (29)
\]

- American DR option constraint (3).

IV. Case Study

A. Data Preparation and Assumptions

The proposed plan is evaluated on a realistic case of the Nordic market. Hourly market prices are available [24]. Hence, each period in this paper is considered as one hour. Nevertheless, note that the proposed method is also applicable on shorter time horizons.

Similar to leading studies in this area [1], [3], price and wind power scenarios are characterized using ARIMA models. A time series of the spot prices of the Nordic market, spanning January 2012 is used to generate price scenarios [24]. Overall, 20 day-ahead price scenarios are generated in stage 1. In addition, four positive and negative imbalance factors are randomly generated. For positive factors, scenarios range between 0.95
and 1 (0.95 ≤ \( S^{\text{pos}}(w) \) ≤ 1), while for negative factors they are between 1 and 1.05 (1 ≤ \( S^{\text{neg}}(w) \) ≤ 1.05).

The wind power producer Hemmet, located in Denmark, is chosen [25]. The installed capacity of this farm is 27 MW (Vestas Turbines). Wind speed scenarios are generated using the ARMA model where the available data in 2012 is used as input time series. 14 wind speed scenarios are generated in stage 1. These scenarios are then transformed to power scenarios using the Vestas Wind curve [26].

Overall, the total number of generated scenarios is 1120, which is calculated by the product of the numbers for day-ahead prices (20 scenarios), imbalance charges/payments (4 scenario-based factors) and wind power production (14 scenarios). This is derived using the method presented in [27]. To this end, the number of scenarios is increased until the objective function is stabilized. In this way a tradeoff between the tractability of the problem and the accuracy of the results is taken into account.

Fig. 3 shows the expected day-ahead price and wind power production. The day-ahead price involves two peak periods, just before Noon and during the evening. Wind power peaks however occur around midnight and the afternoon.

In stage 2, the day-ahead prices are known. However, wind power production and imbalance prices are still unknown. Wind power scenarios of stage 2 are obtained through reducing the number of scenarios generated in stage 1 to 7 scenarios. Indeed, those scenarios having higher deviations from the expected wind power depicted in Fig. 3 are removed. This is reasonable as the wind uncertainty in stage 2 is lower than that of stage 1. Imbalance price scenarios in stage 2 are considered the same as scenarios in stage 1.

DR information is as follows. Since DR contract data are not available, their details are assumed in this paper. However, in order to reasonably model these contracts, two main points are taken into account: first, the prices considered for DR contracts are chosen in a way that they are close to the average of market prices, shown in Fig. 3. Secondly, the DR contracts are assigned in such a way that when the wind power producer is in its high production periods and market prices are low, it most likely sells a part of its energy through DR contracts. On the other hand, when the market price is high, the wind power producer is assumed to be mostly a DR buyer in order to compensate its deviations during this time. Six fixed DR agreements are considered. The first contract covers 1 am to 5 am, where the wind power producer sells energy to the aggregator. The producer buys fixed DR in the next two contracts (6 am–12 pm). In fixed DR contract 4, the producer again sells energy to the DR aggregator (1 pm–4 pm). In the remaining contracts the wind power producer is a fixed DR buyer. Six flexible DR agreements are also modeled. Time horizon for each contract is the same as fixed DR contracts. It is assumed that the wind power producer is able to sell/buy up to 8-MWh flexible DR in each period. Finally, two American and two European DR options are used, where the wind power producer buys these options from the aggregator. The periods in which these options are used are 9 am–12 pm and 5 pm–8 pm. Note that the penalty of not exercising each option is assumed to be equal to 10% of the contract cost. The maximum available DR and DR price ranges are provided in Table I.

### B. Numerical Results and Discussions

1) Decisions in Stage 1: The given problem is mixed-integer linear programming, which is solved for various risk levels using CPLEX 11.1.1 under GAMS [28].

The expected profit vs. the standard deviation is displayed in Fig. 4. It is obvious that while the risk-neutral wind power producer gains more profit with the cost of a higher profit deviation, risk-averse producers prefer a lower profit deviation and consequently obtain a lower profit.

Fig. 5 provides day-ahead offers for various risk levels. The risk-neutral wind power producers sell as much as possible in the day-ahead market. This sale however decreases as the risk level grows. That is, risk-averse producers refuse to sell the majority of their power in the day-ahead market, where they prefer...
Fig. 5. Offers in the day-ahead market.

Table II
FIXED DR CONTRACTS

<table>
<thead>
<tr>
<th>( \rho )</th>
<th>Set Contracts</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>FC2, FC4, FC5, FC6</td>
</tr>
<tr>
<td>0.2</td>
<td>FC2, FC4</td>
</tr>
<tr>
<td>0.4</td>
<td>FC2, FC4</td>
</tr>
<tr>
<td>0.7</td>
<td>FC2, FC4</td>
</tr>
<tr>
<td>1</td>
<td>FC2, FC4</td>
</tr>
</tbody>
</table>

Table III
SIGNED EUROPEAN DR OPTIONS IN STAGE 1

<table>
<thead>
<tr>
<th>( \rho )</th>
<th>EDRO1</th>
<th>EDRO2</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>9am-12pm</td>
<td>6pm-9pm</td>
</tr>
<tr>
<td>0.2</td>
<td>9am-12pm</td>
<td>6pm</td>
</tr>
<tr>
<td>0.4</td>
<td>9am</td>
<td>6pm</td>
</tr>
<tr>
<td>0.7</td>
<td>-</td>
<td>6pm</td>
</tr>
<tr>
<td>1</td>
<td>-</td>
<td>6pm</td>
</tr>
</tbody>
</table>

However, for higher risk levels, this share decreases where for \( \rho = 1 \), flexible DR 2 is not applied. This decrement indeed follows the same rule as fixed DR and DR options.

2) Decisions in Stage 2: This section delivers the results of stage 2 for the risk-neutral (\( \rho = 0 \)) and the risk-averse (\( \rho = 1 \)) wind producers.

Figs. 6 and 7 depict the offers in the balancing market for \( \rho = 0 \) and \( \rho = 1 \), respectively. The sale by the risk-neutral wind power producer is very low in most periods. There are even some periods in which the producer buys energy from the balancing market. This trend is opposite for the risk-averse producer, where a high amount of power is sold in each period. This outcome confirms the tendency obtained in the day-ahead market shown in Fig. 5. That is, while the risk-neutral wind power producer is willing to sell more energy in the day-ahead market, the risk-averse producer prefers low risks and consequently submits more energy to the balancing market, where more precise predictions of power production as well as real-time prices are available.

Fig. 8 provides the total sold power of both wind power producers. The volume is identical for almost all periods. However, it can be seen that the risk-neutral wind power producer has a higher sale share during the peak periods of the price and wind power production (See Figs. 3 and 8), where this is more evident at 9 am, 3 pm and 5–10 pm. This result indicates that risk-neutral wind power producers have a higher tendency to buy DR than do risk-averse producers.

DR outcomes are as follows. All signed European DR in the first stage are exercised in stage 2 by both risk-neutral and risk-averse wind power producers. This is also the result for American DR options. Note that in this stage, ADRO 1 and 2 are exercised at 9 am and 6 pm, respectively. This indeed coincides with peak price periods shown in Fig. 3.
Fig. 7. Imbalance power for $\rho = 1$.

Fig. 8. Total power sold in the market for $\rho = 0$ and $\rho = 1$.

The usage distributions of all flexible DR agreements, except flexible DR 4, are the same as stage 1 for both risk levels. The distributions of flexible DR 4 (Flex4) in stages 1 and 2 for the risk-neutral and the risk-averse wind power producers are delivered in Figs. 9 and 10, respectively. In both cases, the wind power producer changes the usage configurations in stage 2. It can be seen that in this stage the whole flexible DR 4 is used in one period. These results confirm a significant difference in sale shares of the risk-neutral and risk-averse wind power producers at relevant hours in Fig. 8. It can be seen that while the risk-neutral producer has a much higher sale at 3 pm, this happens at 1 pm for the risk-averse producer.

V. CONCLUSIONS

This paper presents a new wind offering plan in the day-ahead market. This plan includes two stages in which a wind power producer employs DR to alleviate its production uncertainty as well as market price violations. The first stage takes place on the day-ahead market, where the producer determines its offer in this market and simultaneously arranges various DR contracts with DR aggregators. The second stage is a successive process which is held right before each dispatch period. In this stage the wind power producer participates in the balancing market. The offer in this market is obtained while at the same time proper DR agreements are finalized. To include DR, a new scheme is proposed in which the wind power producer can set various DR agreements, called fixed DR, flexible DR, American DR options and European DR options with DR aggregators.

The proposed plan is evaluated on a case of the Nordic Market. A stochastic mixed-integer profit function is proposed for each stage which is solved using GAMS. The main findings are as follows. 1) The proposed two-stage plan allows wind power producers to better participate in both day-ahead and balancing markets. 2) While risk-neutral wind power producers prefer to sell most of their energy in the day-ahead market, risk-averse producers have a higher share in the balancing market. 3) In the proposed plan, a wind power producer can arrange various DR contracts in stage 1 and then manage them in stage 2 to better cope with its uncertainty.

Finally, we should emphasize that this paper models the bilateral DR contracts rather than a pool-based exchange. Indeed, the pool-based exchange is still not applicable in many markets since there are various barriers making DR providers reluctant to directly participate in the market. However, setting bilateral contracts with DR purchasers is more practical as there are real cases in Australia, Canada and the USA [22]. Note that by the enough growth of the DR market, it is expected that both bilateral and pool-based DR markets become active. To this end, the level of the risk taken by the wind power producer is the matter of concern. That is, if the producer is risk-neutral, it prefers to
more risk averse, the share of bilateral contracts increases.

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Wind offering strategy in the Australian National Electricity Market: A two-step plan considering demand response

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A B S T R A C T

This paper proposes an energy offering strategy for wind power producers. A new trading plan is presented through which a wind power producer can employ demand response (DR) to maximize its profit. To consider DR, a new DR scheme is developed here. The proposed plan includes two steps: The first step takes place on a day-ahead basis. The corresponding decisions involve an initial offering schedule and preliminary DR arrangements for the following day. The second step coincides with the day of the energy delivery. A consecutive approach is proposed in which the wind power producer determines its final energy offer during each trading interval. Simultaneously, the required DR agreements for that interval are also confirmed. This approach is repeated until all periods of the day are covered. The proposed plan is formulated as a stochastic programming approach, where its feasibility is evaluated on a case of the Australian National Electricity Market (NEM).

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1. Introduction

1.1. Literature review, contributions and approach

Wind power is identified as a leading renewable energy resource. Various incentive schemes and policies are provided to facilitate the application of wind energy worldwide. The European Union has a target of achieving 20% of renewable energy by 2020. The Renewable Energy Target (RET) in Australia also sets the same requirement by 2020. U.S states have distinct goals. For instance, California is planning to obtain 33% of its energy from renewable technologies by 2020 [1].

It is expected that wind power producers could be treated as similar to conventional generators in the near future. This is currently valid for some wind power producers in Germany [1], while it is voluntary in some markets such as the Spanish [2] and Midwest ISO (MISO) markets [1]. In this way, wind power producers are responsible for their production deviation in the market. Two main practical solutions for this issue are presented in some studies: Optimal trading strategies and a joint operation of wind power producers and easily controllable resources.

Optimal trading strategies are addressed in some investigations such as [3–7]. Authors in [3,4] determine the energy level contracted in a short-term market in order to minimize imbalance costs. Authors in [5,6] propose a new short-term trading strategy which includes various trading floors. Finally, authors in [7] evaluate the offering strategy of a price-maker wind power producer in balancing markets.

With regards to joint operation strategies, Ref. [2] illustrates the coordination of wind power producers and pumped-storage units. A joint planning and operation strategy of wind power producers and hydro power plants is provided in [8–10]. The coordination of wind producers and storage systems is described in [11]. Finally, the cooperation of wind power producers and thermal plants is addressed in [12]. Demand response (DR) is another source, which can be used in a joint operation with wind power producers. Relevant studies in literature mostly provide the joint operation of DR and wind power producers to improve network and market operations [13–17]. Few papers investigate DR applicability from wind power producers’ point of view. For instance, authors in [18] investigate smart grid roles in activating passive loads to mitigate wind power variations.

This paper explores both aforementioned areas for wind power producers in the Australian National Electricity Market (NEM) context. A two-step offering strategy is proposed, which allows wind power producers to decide how to trade their production in the market while employing demand response (DR).

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Preliminary decisions are taken on the day prior to the energy delivery (step 1). To this end, a stochastic programming approach is formulated through which initial energy offers and DR agreements are obtained. These decisions are made while both market prices and wind power production are uncertain. To model the risk associated with this uncertainty, conditional Value-at-risk (CVaR) is used.

The second step covers the decisions taken at the real-time dispatch. A successive approach is applied, which runs for each dispatch interval until all intervals are covered. The volume of energy to be offered for each interval is determined. In addition, the wind power producer approves its final DR agreements for the relevant interval. Again, a stochastic programming problem is formulated for this step in which the power production and market price are known for the current interval, but they are still uncertain in the remaining intervals. Similar to step 1, CVaR is used here to assess the risk.

In order to include DR in the given offering plan, a new scheme is proposed in which DR is treated as a public good. Wind power producers are able to trade DR with DR aggregators through various agreements: Fixed DR contracts are proposed, which allow wind power producers to trade a certain DR volume for a given price during a specific period. Flexible DR agreements are formulated in a way that wind power producers set the contract in step 1 and still have flexibility to manage the contract in the real-time usage, i.e. step 2. Finally, by adapting the well-known financial options concept [19,20], a new type of contract, called DR options, is proposed here.

The given DR arrangement is a new scheme as there is no such work in literature addressing a similar model. The majority of DR studies focus on the basic concept [21,22], technical aspects [23], incentive-based DR programs [24,25] and price-based DR actions [26]. Only authors in [27,28] investigate a mechanism through which DR is traded as a commodity. However, their method considers a pool-based DR exchange rather than bilateral contracts. Indeed, pool-based exchange is still not applicable in most markets including Australia, since there are various barriers making DR providers reluctant to directly participate in the market. However, setting bilateral contracts with DR purchasers is more practical as there are real cases in Australia, Canada and the USA [29]. Note that by enough growth in the DR market, it is expected that both bilateral and pool-based DR markets become active. To this end, the level of risk taken by the wind power producer is a matter of concern. That is, if the producer is risk-neutral, it prefers to trade more in the pool-based DR market. However, as it becomes more risk-averse, the share of bilateral contracts increases. Indeed, enhancing both bilateral contracts and pool-based DR market will result in a competitive DR market, which leads reasonable DR prices.

Considering the above overview, the contributions of this paper are as follows.

1. A short-term energy strategy is proposed, which allows a wind power producer to maximize its profit by employing DR agreements in a two-step offering plan.
2. A new DR scheme involving distinct DR derivatives is proposed.

Each DR is introduced with unique features and formulated using proper mathematical equations.

1.2. Australian National Electricity Market vs. other markets

A trading day in the Australian NEM [30] begins at 4:00 am and ends at 4:00 am of the next day. Each trading period represents a half hourly period, which comprises six 5-min dispatch intervals. According to the NEM, generators place their bid at 12:30 pm on the day before the energy delivery. Then, they are allowed to rebid their energy volume up until 5 min prior to the dispatch.

On the other hand, pool markets such as the Nordic, German and Spanish markets mostly comprise a day-ahead market, adjustment (intraday) markets and a balancing (regulating) market. In the Nordic [3], for instance, the day-ahead market is closed at 12:00 pm the preceding day. Additionally, the market involves an adjustment market, called Elbas. This market opens at 15:00 on the same day and lasts up until 1 h prior to the delivery. Finally, the market operator guarantees real-time balances through the regulating market which takes place just before the delivery.

From the above background, it can be emphasized that the proposed plan in this paper is well suited to the Australian NEM. Nevertheless with some modifications, this plan can be generalized to suit other markets. A brief description on this issue is addressed in the conclusion section while the formulations and results will be presented in our future work.

1.3. Paper organization

The rest of the paper is structured as follows. First, the proposed DR scheme is presented in section 2, where each DR contract is introduced and formulated. Then, Section 3 explains the proposed two-step trading plan, where relevant mathematical formulations for each step are provided. Section 4 presents the input data and analyzes the results. Section 5 concludes the paper. The last section (Appendix) provides CVaR descriptions.

2. Comprehensive DR scheme

The following assumptions are considered in the proposed DR scheme. This paper assumes a DR aggregator which is willing to bilaterally trade DR with a wind power producer. It is also assumed that the wind power producer is not involved in the technical aspects of DR. In fact, the DR aggregator is responsible for obtaining DR from consumers. A similar case exists in Australia, where TransGrid buys DR from EnerNOC [29] without concerning the details of DR.

The following DR contracts are formulated in the proposed DR scheme:

2.1. DR option

A wind power producer can arrange a DR option contract with a DR aggregator. Each DR option is determined with a certain DR volume and price for a given period. This agreement gives the producer a right but not an obligation to purchase DR. That is, the wind power producer signs this contract in step 1. However, exercising the contract at energy delivery time (step 2) depends on whether it is profitable or not. If the contract is not carried through in step 2, the wind power producer has to pay a predetermined fee to the DR aggregator as the penalty of not exercising the contract. Fig. 1 shows the structure of a typical DR option.

The cost function of the DR option (DRO) for each step is formulated as follows. Note that all variables and parameters for mathematical formulations throughout the paper are defined in the nomenclature.

Step 1: This step determines whether DR option is signed or not. This decision is indicated by the binary variable $\text{Sgn}_o(t) \in \{0,1\}$. Zero specifies that the wind power producer does not sign the contract, while 1 means the contract is set in this step.

$$C^{\text{DRO,SI}}_o(t) = P_o(t) \cdot \lambda_o(t) \cdot \text{Sgn}_o(t) \cdot d(t) \quad \forall o = 1, 2, \ldots N_o$$  \hspace{1cm} (1)

Step 2: This step is valid for those DR options signed in the previous step, i.e. $\text{Sgn}_o(t) = 1$. Indeed, step 2 decides the exercising
status of these signed contracts. To this end, the binary variable \( v_0(t) \) is used, which is equal to 1 if the contract is exercised and zero if not.

\[
C_{O}^{DRO,S2}(t) = \text{Sgn}_0(t) \cdot [P_0(t) \cdot \lambda_0(t) \cdot v_0(t) \cdot d(t) + (1 - v_0(t)) \cdot f_0^{\text{pen}}(t)]
\]

\( \forall o = 1, 2, \ldots, O \)  

(2)

2.2. Fixed DR

A fixed contract is an agreement between a buyer and a seller of an asset which is traded in the future [19]. Considering this concept, a fixed DR contract is proposed here through which the wind power producer buys this contract from DR aggregators. It is assumed that the producer directly negotiates with aggregators for a mutually attractive deal.

Fixed DR contracts are offered in various blocks, where each block is defined with a specific energy volume and price. The cost of block \( b \) of fixed DR \( f \) is given in (3). Expression (4) shows the margin size of each contract’s block.

\[
C_{FDR}^{f,b}(t) = p_{FDR}^{f,b}(t) \cdot \lambda_{FDR}^{f,b}(t) \cdot d(t) \quad \forall f = 1, \ldots, N_{FDR} \quad \forall b = 1, \ldots, N_{BDR}
\]

(3)

\[
p_{\text{FDR, MIN}}^{f,b}(t) \leq p_{\text{FDR, MAX}}^{f,b}(t)
\]

(4)

Note that once the wind power producer sets a fixed DR contract in step 1, it has to apply it during real time. That is, the volume of the contract set in step 1 remains constant in the next step.

2.3. Flexible DR agreement

Flexible DR agreements are proposed to give the wind power producer a chance to better cope with the uncertainty of its power production as well as spot price violations. When both parties (wind power producer and DR aggregator) set this contract in step 1, they negotiate on the energy volume, price and duration of the agreement. However, during the delivery time (step 2) the wind power producer is able to change the usage distribution of the contracted DR volume during the contract period. That is, the wind power producer is able to distribute the DR usage over the contract period to cope with its uncertainty and achieve a higher profit.

The cost of the flexible DR agreement in step 1 is formulated in (5). Note that \( U_P^{f,b}(t) \) is a binary parameter indicating the periods in which the flexible DR flex is valid. The size of each flexible DR is imposed by (6).

\[
c_{\text{flex, S1}}^{f,b}(t) = p_{\text{flex, S1}}^{f,b}(t) \cdot \lambda_{\text{flex, S1}}^{f,b}(t) \cdot U_P^{f,b}(t) \cdot d(t) \quad \forall f = 1, \ldots, N_{\text{flex}}
\]

(5)

\[
p_{\text{flex, MIN}}^{f,b}(t) \leq p_{\text{flex, MAX}}^{f,b}(t) \quad \forall f = 1, \ldots, N_{\text{flex}}
\]

(6)

A similar cost function is defined for step 2 where symbol S1 is replaced by S2 to represent the relevant formulations for that step. However, an additional constraint is required in step 2, as represented in (7). Indeed this constraint enforces that the overall volume of each flexible DR used in step 2 must be equal to its volume contracted in step 1 \( (E_{Agrd,S1}) \). Note that SP and EP represent the start and end of the period that flexible DR flex is valid.

\[
\sum_{t=\text{EP}}^{\text{SP}} p_{\text{flex, S2}}^{f,b}(t) \cdot d(t) = E_{Agrd,S1}(t) \quad \forall f = 1, \ldots, N_{\text{flex}}
\]

(7)

3. The proposed trading plan

The proposed offering plan is expressed in two steps as shown in Fig. 2. This plan is adjusted to the Australian NEM, where the pre-dispatch process closes at 12:30 pm on the day prior to the energy delivery (step 1) and then, generators are able to change the volume of their offer up until 5 min before the dispatch (step 2). Note that Ancillary services markets are not modeled here. It is assumed that the wind power producer is price-taker in the market. In addition, although other resources such as conventional power plant can be useful for compensating wind power uncertainty, our focus is on using DR for this purpose. Note that DR takes an advantage over the conventional plants in that its response is fast. Nevertheless, it is obvious that DR prices need to be as competitive as other resources to be employed by the wind power producer. A further assumption is that the wind power producer is treated as similar to conventional power plants (scheduled generators in the NEM) [31], where it is responsible for its bidding strategy and production variations. In addition, similar to [4] this paper aims to determine the optimal offering quantities instead of presenting bidding curves which is investigated in [5]. Moreover, this paper assumes a single-node market in which transmission networks are not modeled. This is a common practice in bidding strategy problems investigated in the literature [25,32]. Note that modeling transmission networks needs a bilevel problem formulation through which the upper-level problem represents the wind power producer objective, while the lower-level model addresses the security-constraint unit commitment represented by the ISO [33,34]. We will indeed study this problem in our future work. Finally note that this paper considers DR trading in both directions, i.e. from the DR aggregator to the wind power producer and in the opposite direction. To this end, in case of power shortage, the wind power producer can be a DR

![Fig. 1. The structure of a typical DR option.](image1)

![Fig. 2. The proposed offering plan.](image2)
buyer while during excess production, the producer can sell energy to the DR aggregator.

3.1. Step 1: initial offering

This step takes place at 12:30 pm the preceding day. The wind power producer runs a preliminary strategy here. The producer achieves the initial offering schedule over all periods of the next day \((t = 1, 2, \ldots, \text{Fl})\). In addition, fixed DR contracts are negotiated. Furthermore, the wind power producer determines the periods in which DR options are signed. Finally, flexible DR agreements are set. These decisions are taken under the uncertainty of spot prices and wind power production. Indeed, these parameters are stochastically modeled through a set of scenarios which represent their plausible realizations.

The profit function \((PF)\) formulated for step 1 is given in (8).

The first term of the profit function shows the expected revenue obtained from selling energy to the spot market. The next three terms indicate the cost of the proposed DR agreements. The last component is CVaR [35] which is weighted using the risk factor \((\rho)\) (See a detailed description of CVaR in Appendix). Note that the risk level \((\rho = [0, \infty))\) represents the trade-off between the expected profit and the risk. A risk-averse wind power producer willing to minimize the risk chooses a large value of the risk. On the other hand, a risk-neutral producer prefers higher profits and consequently selects a risk factor close to 0. Note also that although DR contracts are represented as cost terms in the objective function, they may have revenue components when the wind power producer sells energy to the DR aggregator.

Constraints (9) and (10) impose the size limits of power traded in fixed DR and flexible DR agreements, respectively. Expressions (11) and (12) represent the CVaR constraints. These constraints are used to linearize CVaR [35]. Finally, power balance is satisfied in (13), where the offered power to the market must be equal to the wind power production \((P^{w, S1}(t, w))\) plus the power procured from DR. Indeed, this constraint ensures that the decisions on initial wind power offer and DR agreements are valid for each power production scenario.

Maximize \(PF = \sum_{w=1}^{N_w} \pi(w) \cdot \sum_{t=1}^{\text{Fl}} P^{w, S1}(t, w) \cdot \lambda^{w, S1}(t) \cdot d(t) - \sum_{t=1}^{\text{Fl}} \sum_{b=1}^{N_b} C^{\text{DR}, S1}(t) - \sum_{t=1}^{\text{Fl}} \sum_{f=1}^{N_f} \sum_{b=1}^{N_b} e^{FDR}(t) + \sum_{t=1}^{\text{Fl}} \sum_{f=\text{flex}}^{N_f} e^{\text{flex}}(t) + \rho \cdot \left( \xi - \frac{1}{1 - \beta} \sum_{w=1}^{N_w} \eta(w) \cdot \pi(w) \right) \) subject to,

\[
P^{\text{DR,MIN}}_{f,b} \leq P^{\text{DR,MIN}}_{f,b} \leq P^{\text{DR,MAX}}_{f,b}
\]

\[
P^{\text{DR,MIN}}_{\text{flex}} \leq P^{\text{DR,MIN}}_{\text{flex}} \leq P^{\text{DR,MAX}}_{\text{flex}}
\]

\[
\begin{align*}
&\sum_{t=1}^{\text{Fl}} P^{w, S1}(t, w) \cdot \lambda^{w, S1}(t) \cdot d(t) + \sum_{t=1}^{\text{Fl}} \sum_{b=1}^{N_b} C^{\text{DR}, S1}(t) + \sum_{t=1}^{\text{Fl}} \sum_{f=\text{flex}}^{N_f} e^{\text{flex}}(t) + \rho \cdot \left( \xi - \frac{1}{1 - \beta} \sum_{w=1}^{N_w} \eta(w) \cdot \pi(w) \right) \\
&\eta(w) \geq 0; \quad \forall w = 1, 2, \ldots, N_w
\end{align*}
\]

3.2. Step 2: optimal offering

Step 2 deals with the actions required to modify the decisions made in the previous step (see Fig. 2). It begins from 4:00 am and runs for each 5-min dispatch interval. We assume that the wind power offer in this step is accepted by the market operator. This is reasonable since wind power producers usually place their offer in low prices.

This step employs a successive algorithm which iterates from interval 1 to the final interval. For each interval, the following decisions are made. (1) The optimal offering energy for the current interval is determined. (2) It is decided whether the signed DR options in step 1 are exercised for that interval. (3) The required volume of flexible DR for the relevant interval is decided.

To this end, a new profit function is formulated which is solved for each iteration.

Maximize \(PF = \text{Prof}(t)_{\text{CI}} + \text{EProf}(t) | + \rho \cdot \text{CVaR} \)

where,

\[
\text{Prof}(t)_{\text{CI}} = \left[ P^{w, S2}(t) \right]_{CI} \left( t \right) = \left[ P^{w, S1}(t) \right]_{CI} + \text{EProf}(t) |
\]

subject to,

\[
P^{\text{DR,MIN}}_{\text{flex}} \leq P^{\text{DR,MIN}}_{\text{flex}} \leq P^{\text{DR,MAX}}_{\text{flex}}
\]

\[
\begin{align*}
&\sum_{t=1}^{\text{Fl}} P^{w, S2}(t, s) \cdot \lambda^{w, S2}(t, s) \cdot d(t) + \sum_{t=1}^{\text{Fl}} \sum_{b=1}^{N_b} C^{\text{DR}, S2}(t) + \sum_{t=1}^{\text{Fl}} \sum_{f=\text{flex}}^{N_f} e^{\text{flex}}(t) + \rho \cdot \left( \xi - \frac{1}{1 - \beta} \sum_{w=1}^{N_w} \eta(w) \cdot \pi(w) \right) \\
&\eta(s) \geq 0; \quad \forall s = 1, 2, \ldots, N_s
\end{align*}
\]

\[
\begin{align*}
&\sum_{t=1}^{\text{Fl}} P^{w, S2}(t, s) \cdot \lambda^{w, S2}(t, s) \cdot d(t) + \sum_{t=1}^{\text{Fl}} \sum_{b=1}^{N_b} C^{\text{DR}, S2}(t) + \sum_{t=1}^{\text{Fl}} \sum_{f=\text{flex}}^{N_f} e^{\text{flex}}(t) + \rho \cdot \left( \xi - \frac{1}{1 - \beta} \sum_{w=1}^{N_w} \eta(w) \cdot \pi(w) \right) \\
&\eta(s) \geq 0; \quad \forall s = 1, 2, \ldots, N_s
\end{align*}
\]
The proposed offering plan is evaluated on a realistic case of the South Australian (SA) jurisdiction within the Australian NEM. The available spot price and wind speed data are half-hourly resolution. Hence, it is assumed that each given interval in this paper is 30 min [36]. The spot price and wind power production are uncertain parameters and thus they are characterized using proper scenarios. Similar to the relevant studies [5], ARIMA models are chosen for generating price scenarios. A time series of the spot prices of SA from December 2011 to January 2012 is used to generate price scenarios [36]. As a result, 40 price scenarios are generated for step 1.

The wind power producer Lake Bonney 2 is chosen [37]. This producer is located at Mt Gambier AERO and its installed capacity is 159 MW (53 of Vestas 3 MW Turbines). In order to provide wind power scenarios, first, wind speed scenarios are generated using the ARMA model [5,32,38]. To this end, the summer season data from 2007 to 2012 is used as the input time series. 20 wind speed scenarios are generated for step 1. These scenarios are then transformed to power scenarios using the Vestas Wind curve.

Note that the proper number of scenarios is usually determined by one of the following methods. (1) The first method uses scenario reductions techniques [35]. To this end, the original number of scenarios is reduced in a way that makes the problem tractable while keeping it accurate. Fast-forward scenario reduction is the most popular one. (2) The second method follows the same aim, but it targets the objective function. That is, the number of scenarios is increased until the expected profit is stabilized [39]. This paper uses this method, where altogether 800 scenarios are generated. Fig. 3 verifies this number by illustrating the expected profit versus the number of scenarios for the risk-neutral and risk-averse wind power producers.

Fig. 4 displays the expected values of wind power and spot price scenarios in step 1. It can be seen that while the wind power production peak occurs during the first intervals, spot prices see their peak in the afternoon.

\[
ps^{S2}(t, s) = p^{w,S2}(t, s) + \sum_{f=1}^{N_{flex}} \sum_{b=1}^{N_{flex}} p^{f,b}(t) + \sum_{a=1}^{N_{flex}} P_a(t) \cdot Sgn_a(t) \cdot v_a(t) + \sum_{flex=1}^{N_{flex}} p^{DR,S2}(t) \cdot UP^{DR}_{flex}(t)
\]

The given profit function comprises three main terms:

1. The profit obtained in the current interval \((t = \text{CI})\). This function is shown in (15), where it involves the revenue obtained from selling energy into the spot market minus the cost of DR options and flexible DR. Note that since the current interval is very close to the real time dispatch, the spot price and wind power production are assumed to be deterministic parameters here. Thus the obtained profit for the current interval is not associated with uncertainty.

2. The expected profit over the following periods until the final interval \((t = \text{CI} \rightarrow \text{Fl})\). Eq. (16) provides this function. The price and wind forecasts for the following intervals involve a level of uncertainty. Therefore, these parameters are illustrated using generated scenarios.

3. The CVaR risk measure which is shown in (17).

Note that the fixed DR volume determined in the previous step is used in step 2 without any changes. Thus it is not included in the profit function in this step.

The profit function is subject to constraints (18)–(22). Constraint (18) enforces the size limitation of each flexible DR. In addition, Eq. (19) indicates that the total energy volume of each flexible DR must be equal to the contracted volume \(D^{\text{Agd}}(t)\) obtained in step 1. Expressions (20) and (21) show CVaR constraints. Finally, Eq. (22) imposes the power balance. Note that in this constraint, wind power production \((P^{w,S2}(s, t))\) is known for the current interval. However, it is uncertain in the following intervals. In addition, it is important to emphasize the necessity of including the fixed DR volume in the power balance constraint in step 2.
With regards to step 2, the given price and wind scenarios of step 1 are reduced to 20 and 10, respectively. For this purpose, those scenarios of step 1 which have higher levels of deviations from the average values shown in Fig. 4 are removed. This is reasonable since step 2 is closer to the trading intervals and hence its uncertainty is lower than that of step 1.

The information of DR contracts is provided in Table 1. Since DR contract data are not available, their details are thoughtfully assumed in this paper. In order to reasonably model these contracts, two main points are taken into account: first, the prices considered for DR contracts are chosen in a way that they are close to the expected price scenarios, which is shown in Fig. 4. Secondly, the DR contracts are assigned in such a way that when the wind power producer is in its high production periods and market prices are low, it most likely sells a part of its energy through DR contracts. On the contrary, when the market price is high, the wind power producer is assumed to be mostly a DR buyer in order to compensate its deviations during this time.

Table 1
<table>
<thead>
<tr>
<th>DR contracts details</th>
<th>Fixed DR</th>
<th>Flexible DR</th>
<th>DR options</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intervals (interval)</td>
<td>3–48</td>
<td>1–48</td>
<td>1–48</td>
</tr>
<tr>
<td>Price ranges ($/MWh)</td>
<td>24–44</td>
<td>20–40</td>
<td>30–44</td>
</tr>
<tr>
<td>Volume ranges (MW)</td>
<td>Sell up to 12</td>
<td>Sell up to 20</td>
<td>Sell up to 10</td>
</tr>
<tr>
<td></td>
<td>Buy up to 15</td>
<td>Buy up to 20</td>
<td>Buy up to 20</td>
</tr>
</tbody>
</table>

Fig. 4. Expected wind power production and spot prices.

Fig. 5. The expected profit vs. standard deviation.
Twelve fixed DR contracts are considered. The first three contracts cover the time intervals between 3 and 18. According to the above description, the wind power producer can sell energy to the aggregator in these periods. The other contracts consider the remaining intervals where the wind power producer buys fixed DR from the DR aggregator. Six flexible DR agreements are modeled. The wind producer is able to sell/buy up to 20 MW flexible DR in each interval. Finally, four DR options are taken into account, where the penalty of not exercising each option is assumed to be equal to 15% of the contract cost. Note that this penalty is derived according to the common fee used in financial markets [19]. It is assumed that the wind power producer can sell energy through DR options in the first 18 intervals while it is a DR option buyer during the following periods.

### 4.2. Numerical results

#### A. Decisions on step 1 (S1)

The given problem is mixed-integer linear programming which is solved using CPLEX 11.1.1 under GAMS [40].

Fig. 5 displays the expected profit versus the standard deviation for various risk levels. The risk-neutral wind power producer obtains around $23,000 while its profit deviation is just under $15,000. Increasing the risk level leads to a decrement in both values, where for the most risk-averse producer the expected profit and the standard deviation decrease to around $21,000 and $10,000, respectively. In other words, the risk-neutral wind power producer obtains almost 10% higher profit than the risk-averse one with the cost of around 45% higher profit deviation.

Table 2 shows the contracted fixed DR agreements for different levels of the risk. A risk-neutral wind power producer ($\rho = 0$) sets 8 fixed DR contracts out of 12 existing ones. This number declines as the producer becomes more risk averse, where for $\rho = 5$, only 3 contracts are employed. This trend is reasonable as risk-averse producers avoid increasing their risk by purchasing energy from resources such as fixed DR and selling it in the spot market.

Table 3 represents the intervals in which DR options (DRO) are contracted in step 1. All four DROs are signed for different risk levels. However, the number of signed DR options is reduced as the risk level increases. Indeed, the declining trend follows the similar rule as the fixed DR pattern, discussed above. In addition, it can be seen that risk-averse producers are generally DR option sellers, where they sign DR options mostly during intervals 1–18.

The volume of contracted flexible DR agreements is shown in Table 4. The risk-neutral wind power producer buys 195 MWh flexible DR from the aggregator, where all six given agreements are used. Increasing the risk level leads a lower share of flexible DR. This is obvious in $\rho = 0.5$ and $\rho = 1$, where only the first three contracts

<table>
<thead>
<tr>
<th>Table 2</th>
<th>Fixed DR contracts.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho$</td>
<td>Set contracts</td>
</tr>
<tr>
<td>0</td>
<td>FC2, FC4, FC5, FC6, FC7, FC9, FC11, FC12</td>
</tr>
<tr>
<td>0.5</td>
<td>FC2, FC4, FC5, FC6, FC9, FC12</td>
</tr>
<tr>
<td>1</td>
<td>FC2, FC4, FC5, FC6, FC12</td>
</tr>
<tr>
<td>5</td>
<td>FC5, FC6, FC12</td>
</tr>
</tbody>
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<table>
<thead>
<tr>
<th>Table 3</th>
<th>Signed DR options in step 1.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho$</td>
<td>DRO1</td>
</tr>
<tr>
<td>0</td>
<td>8, 10–18, 31–34, 42–44</td>
</tr>
<tr>
<td>0.5</td>
<td>7, 8, 10–18, 32</td>
</tr>
<tr>
<td>1</td>
<td>7–18</td>
</tr>
<tr>
<td>5</td>
<td>8, 10–18</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 4</th>
<th>Contracted Flexible DR in step 1 (MWh).</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho$</td>
<td>Flex1</td>
</tr>
<tr>
<td>0</td>
<td>20</td>
</tr>
<tr>
<td>0.5</td>
<td>20</td>
</tr>
<tr>
<td>1</td>
<td>20</td>
</tr>
<tr>
<td>5</td>
<td>−3.6</td>
</tr>
</tbody>
</table>
are employed and the share of flexible DR decreases to less than half. An interesting point is that the most risk-averse wind power producer \((\rho = 5)\) sells around 175 MWh energy to the DR aggregator. This is sensible since the risk-averse producer can reduce the risk of the spot market by selling a portion of its energy through the reliable flexible DR agreement.

Fig. 6 shows the initial bids for various risk levels. It can be seen that all wind power producers have lower offers than their expected production in the first 18 intervals, particularly between intervals 5 and 18. That is, they prefer to sell a percentage of their expected power through DR contracts. However, for the rest of the intervals the trend is as follows. Risk taker producers, and ultimately the risk-neutral one \((\rho = 0)\), have higher offers than their expected production in intervals after 18. This indicates that they tend to buy DR to resell it to the spot market. However, as the wind power producer becomes more risk averse, this tendency decreases. It can be seen that for these producers the bid is almost equal to or even lower than the wind power expectation. This is sensible since risk-averse producers refuse to have more risk by buying DR and selling it to the spot market as a volatile resource.

B. Decisions on step 2 \((S2)\)

This section delivers the results of step 2 for the risk-neutral \((\rho = 0)\) and the most risk-averse \((\rho = 5)\) wind power producers.
Fig. 7 compares the initial (step 1) and final (step 2) offer curves for the risk-neutral wind power producer \((\rho = 0)\). The initial offer curve is modified in almost all intervals in step 2. In the final offer curve, more power is sold during the first intervals but the share of the following periods decreases. This indeed shows how the risk-neutral producer corrects its initial offers during the real time when more accurate power and spot price expectations are available. It is also obvious that the final offer is almost the same as the expected wind power in the first 18 intervals, while it is higher in the remaining intervals. Indeed, the risk-neutral producer aims to increase its profit though buying DR and selling it to the market in the last intervals.

The distributions of flexible DR employed by the risk-neutral wind power producer in steps 1 and 2 are provided in Fig. 8. Each sub-figure shows the outcome of one flexible DR agreement. Note that X-axis represents the intervals during which each flexible DR agreement is valid. The wind power producer changes the usage configurations of flexible DR contracts 1, 2, 3 and 6 in step 2. Significant modifications are made in contract 2, where the producer applies the majority of the contracted volume during intervals

Fig. 9. DR options not exercised in step 2-Rho = 0.

Fig. 10. The initial offer curve (S1) vs. the final offer curve (S2)-Rho = 5.
13 and 14. Indeed, it can clearly be seen that changes in intervals 13 and 14 have significant impacts on the final offer curve shown in Fig. 7. This is also obvious for interval 23. Note that the decisions made on contracts 4 and 5 remain the same as step 1.

Fig. 9 provides the intervals in which the signed DR options in step 1 are not exercised in the final offer. As can be seen, most of the DR options (DRO) are not exercised during the last intervals. This is more obvious during intervals 42–44, where all four given DRO signed in step 1 are not applied during the final offer. This means that although these DRO agreements are signed in step 1, the wind power producer refuses to use them when the real-time decisions are made. This correction action indeed coincides with the falling trend of the final offer curve during periods 37–48 (See Fig. 7).

The outcomes of the most risk-averse wind power producer are delivered in Figs. 10 and 11. The initial and final offers are depicted in Fig. 10. Similar to the risk-neutral wind power producer, the risk-averse producer makes correction actions in a way to increase its offer in the first intervals while reducing it in the last periods. More specifically, the final offer is higher than the initial one during intervals 15–19. On the other hand, it can be seen that for the intervals 20–48 the wind power producer has a lower offer in step 2. Note that the final offer is lower than the expected wind power production in the first 18 intervals (due to selling a portion of energy to the DR aggregator), while it is almost the same as that in the rest intervals. Note also that the initial and final offer trends of the risk-averse wind power producer are not as much different as the case of the risk-neutral one. This actually indicates how the conservative view of the risk-averse wind power producer affects its initial decisions in step 1.

Fig. 11 represents the modifications of flexible DR usage in step 2 in comparison to that of initial offers. The wind power producer modifies its initial decisions in all flexible DR agreements. This is more obvious in contracts 3 and 4. These modifications are indeed reflected in the final offer (Fig. 10), where for instance significant drops in intervals 20–24 in the final offer coincide with the higher sale of the wind power producer through flexible DR 4.

Finally note that the risk-averse wind power producer finds all signed DR options in step 1 beneficial and hence exercises them in its final offer.

5. Conclusions

This paper presents a new offering strategy for wind power producers, which includes two steps. The first step takes place on the day prior to the energy delivery in which the initial strategies are implemented. The second step is a successive process which is held right before each dispatch interval. In this step the wind power producer modifies its initial decisions to maximize its profit. This strategy allows wind power producers to employ DR. To this end, a new DR scheme is presented through which the wind power producer can buy DR from DR aggregators through various DR agreements.

The proposed plan is evaluated on the Australian National Electricity Market. A stochastic mixed-integer profit function is proposed for each step which is solved using GAMS. The main findings are as follows. (1) The proposed plan is beneficial to wind power producers to cope with their production uncertainty as well as spot market violations. While the decisions made on the preceding day are taken under uncertainty, step two allows the producer to take corrective actions once uncertain parameters are known. (2) The proposed strategy helps wind power producers to benefit from DR agreements. Risk-neutral wind power producers place initial offers in a way to follow both the peak of their power production and spot prices. However, risk-averse producers prefer an offering trend similar to their production pattern. (3) Both risk-neutral and risk-averse wind power producers make correction actions in step 2. This is however more obvious for the risk-neutral wind power producer.

Although the proposed plan is applied to the Australian NEM, with some modification it can be generalized to other markets. Indeed, the formulations need to be changed in order to address both day-ahead and balancing markets. The first step indeed clears the day-ahead market, while the second step balance the
production deviation in the balancing market. This work will be addressed in our future work.

6. Nomenclature

The variables decided in steps 1 and 2 are represented as S1 and S2, respectively.

C. Indices

b  index showing fixed DR’s blocks
f  index representing fixed DR contracts
flex  index representing flexible DR agreements
o  index representing DR options
t  index representing the time interval

D. Variables

E^grad.S1  contracted energy volume of flexible DR flex (S1)
P^f,b(t)  power of fixed DR f, block b (S1)
P^DR.S1 frustrated (t) power of power of flexible DR (S1)
P^DR.S2 frustrated (t) power of power of flexible DR (S2)
P^w.S1(t, w)  initial power offered in the spot market (S1)
P^w.S2(t, s)  final power offered in the spot market (S2)
P^sign(t)  binary variable indicating whether DR option o is signed or not (S1)
P^o(t)  binary variable indicating whether DR option o is exercised or not (S2)
ξ, η(w), η(s)  auxiliary variables for calculating CVaR (S1, S2)

E. Constants

d(t)  duration of time interval t
f^pen(t)  penalty of not exercising DR option o
P^DR,MAX f,b(t)  maximum power of fixed DR f, block b
P^DR,MIN f,b(t)  minimum power of fixed DR f, block b
P^DR,MAX flex(t)  maximum power of flexible DR flex
P^DR,MIN flex(t)  minimum power of flexible DR flex
P^o(t)  power of DR option o
P^w.S1(t, w)  wind power scenario w in step 1
P^w.S2(t, s)  wind power scenario s in step 2
P^UP flex(t)  binary parameter indicating the intervals in which flexible DR flex is valid.
ρ  risk level
β  confidence level (Equal to 0.95)
λ^DR f,b(t)  price of price of fixed DR f, block b
λ^DR flex(t)  price of price of flexible DR flex
λ^w.S1(t, w)  spot price scenario w in step 1
λ^w.S2(t, s)  spot price scenario s in step 2
λ^o(t)  price of DR option o
π(w)  probability of scenario w in step 1 (\(\sum_{w=1}^{N_w} \pi(w) = 1\))
π(s)  probability of scenario w in step 2 (\(\sum_{s=1}^{N_s} \pi(s) = 1\))

F. Numbers

N^BDR  number of blocks of fixed DR contracts
N^FDR  number of fixed DR contracts
N^flex  number of flexible DR agreements
N^o  number of DR options
N^w  number of scenarios in step 1
N^s  number of scenarios in step 2

Appendix

In profit functions, CVaR is defined as the expected value of the profits smaller than the \((1 - \beta)\)-quantile of the profit distribution \((\beta)\) is the confidence level, which is usually taken as 0.95. In other words, CVaR is defined as the expected profit not exceeding Value-at-Risk (VAR) [35]:

\[
\text{CVaR} = \text{Expected profit} \mid \text{profit } \leq \text{VaR}
\]

where,

\[
\text{VaR} = \text{Max}(x \mid \text{probability(profit}(x) \leq x) \leq 1 - \beta)
\]

Hence, the linear formulation of CVaR is [35]:

\[
\text{Max}_{x} \eta(w) \xi - \frac{1}{1 - \beta} \sum_{w} \eta(w) \pi(w)
\]

where, the optimal value of \(\xi\) is VaR. \(\eta(w)\) is equal to the difference between VaR and the profit of scenario \(w\), and \(\pi(w)\) is the probability of scenario \(w\).

Consequently, as CVaR is determined in a maximization function, it should have the same sign, i.e., (+), as the profit function.

References


Modelling demand response aggregator behavior in wind power offering strategies

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HIGHLIGHTS

- This paper proposes a new model to include DR in wind offering strategy.
- A wind power producer is able to trade DR with a DR aggregator.
- The DR aggregator behavior is modelled through a revenue function.
- A bilevel problem is formulated which is transformed into a linear problem.
- The outcomes indicate the usefulness of the proposed strategy.

ABSTRACT

This paper proposes a new wind offering strategy in which a wind power producer employs demand response (DR) to cope with the power production uncertainty and market violations. To this end, the wind power producer sets demand response (DR) contracts with a DR aggregator. The DR aggregator behavior is modeled through a revenue function. In this way the aggregator aims to maximize its revenue through trading DR with the wind power producer, other market players and the day-ahead market. The problem is formulated in bilevel programming in which the upper level represents wind power producer decisions and the lower level models the DR aggregator behavior. The given bilevel problem is then transformed into a single-level mathematical program with equilibrium constraints (MPEC) and linearized using proper techniques. The feasibility of the given strategy is assessed on a case of the Nordic market.

1. Introduction

Determining an optimal offering strategy is the main challenge faced by a wind power producer. This is due to its power production uncertainty as well as market price volatilities. Research in the literature striving to present solutions for this issue mainly focuses on market studies [1–7] and joint operation problems [8–14].

Authors in [1] investigate a probabilistic bidding model for wind power producers. The concept of minimizing imbalance costs in wind offering strategies is investigated in [2,3]. Offering in various market floors including day-ahead, adjustment and balancing markets is addressed in [4]. Ref. [5] recommends the coalition of wind power producers to alleviate the wind power uncertainty. Researchers in [6] evaluate the offering strategy by price-maker

wind power producers. Finally, offering strategy considering two models, i.e. naive use of wind production forecasts and stochastic programming, is addressed in [7].

A joint operation of wind power producers and storage systems is provided in [8–11]. The coordination of wind power producers and hydro power plants is studied in [12,13]. The coordination of wind power producers and thermal power plants is investigated in [14]. Demand response (DR) is now becoming matured around the world. Practical experience worldwide indicates this improved trend. For instance, refer to [15] for the European demonstration, [16] for the US experience and [17] for Italian programs. DR can also be employed by wind power producers as a hedging resource. The literature survey however indicates that relevant studies mostly focus on the coordination of DR and wind power producers to improve network and market operations [18–21].

This paper proposes a new offering strategy through which a wind power producer is able to trade DR with a DR aggregator in order to tackle the uncertainties associated with both power
production and market prices. The wind power producer decides its offer in the day-ahead market while setting DR contracts with the DR aggregator. To this end, the DR aggregator behavior is modeled through a revenue maximization function in which the aggregator determines its DR trading shares with three main resources: the wind power producer in our study, other market players interested in DR, and the day-ahead market. A bilevel problem [22, 23] is formulated in which the upper-level decision maker (leader) is the wind power producer while the lower-level problem is decided by the DR aggregator (follower). The overall problem is then transformed into a single-level mathematical program with equilibrium constraints (MPEC) by replacing the lower-level problem with its Karush–Kuhn–Tucker (KKT) optimality conditions [24]. In addition, the nonlinearities of the derived MPEC are linearized using the strong duality theorem [24] and the technique provided in [25].

A case study of the Nordic market is used to evaluate the validity of the proposed offering strategy. Uncertainties in each level are characterized using a set of finite scenarios. In addition, the risk is carried out using conditional value-at-risk (CVaR).

Overall, the contributions of the paper are as follows.

1. A new model is proposed to include DR in the offering strategy of a wind power producer. Accordingly, the wind power producer is able to participate in a day-ahead market while arranging DR contracts with a DR aggregator to lessen its risk.
2. The competition in the DR procurement is taken into account through modelling the DR aggregator behavior. To this end, a bilevel programming problem is formulated which is then rendered into a single-level linear MPEC using proper methods.

The rest of the paper is structured as follows. Section 2 addresses the proposed wind offering strategy, where the mathematical formulation of the proposed bilevel problem is described. Then the equivalent linear formulation is presented in Section 3. Section 4 provides a case study with numerical results. Section 5 concludes the paper. Finally, appendices are addressed in the last section.

2. Wind offering strategy

2.1. Framework

The following assumptions are made in the proposed strategy. First, it is assumed that the wind power producer makes offers in the day-ahead market while clearing imbalances in the balancing (regulating) market. Additionally, the given wind power producer is treated as similar to conventional power plants [26], where it is responsible for its bidding strategy and power production variation. Moreover, similar to [13], this paper determines the optimal offering quantities instead of presenting bidding curves which is investigated in [4]. A further assumption is that modelling technical DR programs through which the DR aggregator obtains DR from customers is not the focus of this paper. Finally, note that the DR flow can be either from the aggregator to players willing to trade DR or in the opposite direction. In this way, the DR aggregator maximizes its revenue when it is a DR seller and minimizes its cost when buying energy through DR contracts.

The proposed bilevel wind offering strategy is illustrated in Fig. 1. It is considered that the DR aggregator can trade DR with the wind power producer (WPP), other competitors that are willing to trade DR, and the day-ahead market. While parameters in each level are shown by dash line boxes and arrows, decision variables are represented using solid line boxes and arrows. The upper-level problem belongs to the wind power producer (WPP), where it aims to maximize its profit subject to the given constraints as well as the DR volume. Indeed, the obtained DR volume is determined by the DR aggregator in the lower-level problem, where it depends on the price that the wind power producer offers to the aggregator. Thus, the links between the upper-level and lower-level problems are the DR price offered by the wind power producer and consequently, the DR share that the aggregator provides to the wind power producer (double lines in Fig. 1).

The procedure carried out in this strategy is as follows. The wind power producer determines its DR price while taking into account the DR prices offered by other competitors as well as the day-ahead (DA) market price (refer to upper-level problem, top right-hand side). Accordingly, the DR aggregator decides the share of each resource in the lower-level problem. Consequently, given the DR share obtained by the wind power producer, the producer makes its offer in the day-ahead and balancing markets. To this end, besides the price forecasts of DA and Balancing (Bal.) markets, the level of the risk taken by the producer is needed to be taken into account (refer to upper-level problem, bottom left-hand side). That is, depending on how risk averse the producer is, the energy portion to be sold in each market is determined.

Note that the above decisions are made while the problem is associated with the uncertainty of the following parameters: day-ahead market price, balancing market price, wind power production, and the DR price offered by other competitors. These uncertain parameters are represented using finite scenarios. Two distinct sets of scenarios are defined in this paper as follows.

Each upper-level scenario is represented by scenario \( w \), which comprises the vectors of day-ahead price \( (x_{DA}^{w}(t, w)) \), balancing price \( (x_{imb}^{w}(t, w)) \) and wind power production \( P^{w}(t, w) \).

\[
\text{scenario}_w = \{x_{DA}^{w}(t, w), x_{imb}^{w}(t, w), P^{w}(t, w)\}
\]  

Fig. 1. The proposed bilevel wind offering strategy.
The probability of each scenario occurrence equals \( \pi(w) \), where \( \sum_{w \in \Omega} \pi(w) = 1 \).

Each lower-level scenario is shown by scenario \( s \), which involves a vector of other competitors’ prices \( \{x'(t,s)\} \) as well as a day-ahead market price vector \( \{x_{DA}(t,s)\} \).

\[
\text{scenarios} = \{x'(t,s), x_{DA}(t,s)\}
\]  

(2)

Similar to the upper-level problem, the probability of each scenario is \( \pi(s) \), where \( \sum_{s \in \Omega} \pi(s) = 1 \).

2.2. Market model

The proposed offering plan is applied to the Nordic market. This market involves three floors, called the spot (day-ahead) market, Elbas as an adjustment market and the regulating (balancing) market [2]. Elbas is not very active [2] and hence it is not modeled here.

The day-ahead (spot) market closes at 12:00 pm the preceding day of the energy delivery. Then, offers and bids from players are stacked and the day-ahead price is derived. The revenue obtained from the day-ahead market is formulated in (3).

\[
R_{DA}(t,w) = p_{DA}(t) \cdot x_{DA}(t,w) \cdot d(t)
\]

(3)

\( p_{DA}(t) \) is the offered power in the day-ahead market during period \( t \). \( x_{DA}(t,w) \) represents the price of the day-ahead market in scenario \( w \in \Omega \) during period \( t \). \( d(t) \) is the duration of period \( t \).

The balancing (regulating) market is used to balance between production and consumption. To this end, regulation up or down is usually activated. Thus, imbalance price \( x_{imb}(t,w) \) is represented by a pair of positive and negative imbalance prices, i.e., \( \{x_{imb^{pos}}(t,w), x_{imb^{neg}}(t,w)\} \). The relationship between imbalance prices (positive \( x_{imb^{pos}} \) and negative \( x_{imb^{neg}} \)) and the day-ahead price \( x_{DA}(t,w) \) during upward and downward regulation is given as follows [4].

\[
\begin{align*}
\text{Down} & \quad x_{imb^{pos}} \\
\text{Up} & \quad x_{imb^{neg}} \\
\text{Up} & \quad x_{DA} \geq x_{imb^{neg}} \\
\text{Down} & \quad x_{DA} \leq x_{imb^{pos}}
\end{align*}
\]

(4)

An estimation of positive and negative imbalance prices for the Nordic market is provided in [13].

\[
\begin{align*}
x_{imb^{pos}} &= 0.95 \times x_{DA} \\
x_{imb^{neg}} &= 1.05 \times x_{DA}
\end{align*}
\]

(5)

(6)

This paper further extends the given model in a way that the uncertainty of the balancing market is taken into account:

\[
\begin{align*}
x_{imb^{pos}}^{pos} &= S^{pos}(w) \times x_{DA} \\
x_{imb^{neg}}^{neg} &= S^{neg}(w) \times x_{DA}
\end{align*}
\]

(7)

(8)

where \( S^{pos}(w) \leq 1 \) and \( S^{neg}(w) \geq 1 \) are the scenario-based factors of positive and negative imbalance prices respectively. The revenue/cost of the balancing market is then formulated below [4].

\[
R/C_{imb}(t,w) = p^{pos}(t,w) \cdot S^{pos}(w,t) \cdot x_{DA}(t,w) \cdot d(t) - p^{neg}(t,w) \cdot S^{neg}(w,t) \cdot x_{DA}(t,w) \cdot d(t)
\]

(9)

where \( p^{pos}(t,w) \) and \( p^{neg}(t,w) \) are the positive and negative imbalance power in scenario \( w \in \Omega \) and time period \( t \).

2.3. Objective function

The bilevel problem is formulated as follows:

Maximize \( PF = \sum_{w \in \Omega} \pi(w) \cdot \sum_{t \in T} [R_{DA}(t,w) + R/C_{imb}(t,w)] \)

(10)

Subject to

\[
\begin{align*}
0 & \leq p^{pos}(t,w) \leq p^{hi}(t,w) + p^{DR}(t) \\
0 & \leq p^{neg}(t,w) \leq p^{infw} + p^{DR}(t) \\
p^{DA}(t) + p^{imb}(t,w) = p^{DA}(t,w) + p^{DR}(t) \\
p^{imb}(t,w) = p^{imb}(t,w) - p^{imb}(t,w) \\
- \text{Profit}(w) + \xi - \eta(w) & \leq 0; \forall w \in \Omega \\
\eta(w) & \geq 0; \forall w \in \Omega
\end{align*}
\]

(11)

(12)

(13)

(14)

(15)

(16)

(17)

(18)

(19)

where,

\[
\begin{align*}
\text{sp}^{w}(t,s) & \in \arg\max \text{ \sum_{s \in S} \pi(s) \cdot C_{DR}(t) \cdot x_{DA}(t,s) - \sum_{t \in T} \pi(t) \cdot x_{DR}(t)} \\
\sum_{t \in T} \pi(t) \cdot \text{C_{DR}(t) \cdot x_{DA}(t,s)} & + \sum_{t \in T} \text{sp}^{w}(t,s) \cdot x_{imb^{pos}}(t,s) \\
& + \sum_{t \in T} \text{sp}^{w}(t,s) \cdot x_{imb^{neg}}(t,s) & = 1 \quad \text{if } \{b^{t}(t) = 1 \text{ or } b^{t}(t) = 1 \} \\
\text{sp}^{w}(t,s), \text{sp}^{DA}(t,s), \text{sp}^{imb}(t,s) & \geq 0 \quad \text{for all } t, s, c
\end{align*}
\]

(20)

(21)

(22)

The upper level problem indicates the profit maximization of the wind power producer (Eq. (10)). This problem involves the expected revenue obtained from the day-ahead market, the expected revenue/cost of the balancing market, the cost of DR, and the risk measure. \( p^{DR}(t) \) and \( x_{DR}(t) \) are respectively the DR volume obtained and the DR price offered by the wind producer (Eq. (10)). This problem involves the CVaR constraints, which are derived to linearize this risk measure. Note that the risk level (\( \rho = 0 \)) represents a tradeoff between the expected profit and the risk. A risk-averse wind power producer willing to minimize the risk chooses a large value of the risk level. On the other hand, as the wind producer becomes a risk seeker and ultimately a risk-neutral, it prefers higher profits and consequently selects a risk factor close to 0.

The profit function is subject to the following constraints. Positive and negative imbalance offers are limited by (11) and (12), respectively. \( p^{DA}(t,w) \) is wind power production in scenario \( w \) and time \( t \). \( p^{imb}(t,w) \) is the installed capacity of the wind power producer.

The power balance is given in (13). In this equation, \( p^{imb}(t,w) \) is the power traded in the balancing market, which is represented in (14). Expressions (15) and (16) represent conditional value at risk (CVaR) constraints, which are derived to linearize this risk measure. Note that \( \text{Profit}(w) \) in (17) indicates the obtained profit in scenario \( w \). The DR volume is calculated in (18). \( C_{DR}(t) \) is the total available DR capacity that can be traded by the aggregator. As mentioned earlier the DR flow can be either from the DR aggregator to the wind power producer or in the reverse direction. Therefore, the DR capacity is the maximum DR that the aggregator can offer.
can either sell \((P^\text{max}_u(t))\) or buy \((P^\text{max}_l(t))\) (see Eq. (19)). \(b^u(t)\) and \(b^l(t)\) are binary parameters which respectively indicate whether the DR aggregator is a DR seller or buyer in time period \(t\).

\(sp^u(t,s)\) is the DR share percentage that the wind power producer trades with the DR aggregator. Indeed, this share is obtained by the lower level problem which is formulated in (20)–(22). The revenue maximization problem of the DR aggregator is modeled in (20). The DR aggregator trades DR with the wind power producer, the day-ahead market, and other competitors. Note that \(sp^u(t,s)\) represents the DR share percentage of the day-ahead market and \(sp^l(t,s)\) shows the share of competitor \(c \in \{1, 2, \ldots, N_T\}\). Note also that during periods in which the aggregator is a DR buyer, the objective is actually a cost minimization function. Constraint (21) imposes that total DR share percentage must be equal to 1. Finally, constraint (22) is used for variable declarations.

### 3. Linear formulation

The given problem is bilevel programming that includes nonlinearity. This section provides an equivalent single-level linear problem which is easily solvable by commercially available software. To this end, the following procedure is applied.

First, the bilevel problem is transformed into a single-level Mathematical Program with Equilibrium Constraints (MPEC). For this purpose, the lower-level problem is replaced by its first-order optimality conditions through the KKT conditions [24] (Appendix A). Note that this transformation is valid as the lower-level problem is continuous and linear and thus convex. The next step is to linearize the derived MPEC. Indeed, the MPEC is nonlinear which is easily solvable by commercially available software. To complementarity slackness conditions resulting from the KKT optimality conditions through the KKT conditions [24] (Appendix B).

Overall, the equivalent single-level linear program is as:

\[
\text{Maximize PF} = \sum_{w \in L_w} \pi(w) \cdot \sum_{t \in T} \left[ R^{DA}(t, w) + R/c^{\text{min}}(t, w) \right] - \sum_{t \in T} \text{Cost}^{DR}(t) + \rho \cdot \left( \xi - \frac{1}{\beta} \sum_{w \in L_w} \eta(w) \cdot \pi(w) \right) \quad (23)
\]

subject to

\[
\text{Cost}^{DA}(t) = -\sum_{s \in S} \pi(s) \left[ \gamma(t, s) + C^{\text{OR}(t)}(t) \cdot sp^{DA}(t, s) \cdot \lambda^{DA}(t, s) + C^{\text{OR}(t)}(t) \sum_{s \in S} sp^{DA}(t, s) \cdot \lambda^{DA}(t, s) \right] \quad (24)
\]

Constraints \((A2)\)--\((A5)\).

Constraints \((A9)\)--\((A14)\).

The derived problem is a mixed-integer linear programming approach. Constraints \((11)\)--\((19)\), \((21)\) and \((22)\) of the original problem are applied here. Expression (24) shows the linear equivalent of the product of \(P^{DA}(t)\) and \(\lambda^{DR}(t)\), which is obtained from Appendix C (we called it \(\text{Cost}^{DR}(t)\) in (23)). Constraints \((A2)\)--\((A5)\) are associated with KKT optimality conditions (shown in Appendix A). Finally, constraints \((A9)\)--\((A14)\) are used to linearize the complementarity slackness conditions resulting from the KKT optimality conditions (shown in Appendix B).

### 4. Case study

#### 4.1. Data preparation and assumptions

The proposed offering strategy is assessed on a realistic case of the Nordic market. Since hourly market prices are available [27] each period in this paper is considered as one hour. Nevertheless, the presented strategy is also applicable on shorter time horizons.

The upper-level scenarios are generated as follows. 10 price scenarios are generated. For this purpose, similar to leading studies in this area [2,4], the ARIMA method is used. A time series of the spot prices of the Nordic market spanning January 2012 is used to generate price scenarios [27]. In addition, four positive and negative imbalance factors are randomly generated. For positive factors, scenarios range between 0.95 and 1 (0.95 \(\leq S^{\text{pos}}(w) \leq 1\)), while for negative factors, they are between 1 and 1.05 (1 \(\leq S^{\text{neg}}(w) \leq 1.05\)).

The wind power producer Hemmet located in Denmark is chosen [28]. The installed capacity of this farm is 27 MW (Vestas Turbines). The main focus of the paper is to investigate wind offering strategies considering DR. Therefore, wind power scenarios are simply generated while weather conditions and the specific characteristics of wind speed as well as wind turbines are neglected. Wind speed scenarios are generated using the ARMA model where the available data in 2012 is used as an input time series. Accordingly, fourteen wind speed scenarios are generated. These scenarios are then transformed into power scenarios using the Vestas Wind curve. The overall number of scenarios makes a tradeoff between the tractability of the problem and the accuracy of the results [4]. Note that using wind speed and market price data for a longer period will improve the accuracy of the generated scenarios. However, due to the limited access to the wind speed data, this paper uses a short-period data, i.e. January 2012. Note also that for making a better correlation between wind power and market price scenarios, the period of price data is chosen the same as wind speed data.

Fig. 2 shows the expected day-ahead price and wind power production. The day-ahead price involves two peak periods, just before noon and during the evening. Wind power peaks however, occur during midnight and the afternoon.

The lower-level scenarios are generated as follows. Besides the wind power producer, two other competitors (C1 and C2) willing to trade DR with the aggregator are considered. Three price scenarios are generated for each competitor as illustrated in Fig. 3. Competitors are indicated with “C”, while “S” represents the scenarios. Note that these scenarios are generated in a way that they are closed to the day-ahead market price mean shown in Fig. 2. Indeed, the DR aggregator determines the DR share of each individual wind producer.
competitor based on these price scenarios. Note also that day-ahead price scenarios for the lower-level problem are the same as those generated in the upper-level one.

DR is currently in its early stage, where DR data is not publicly available. This paper therefore assumes the DR data as follows. The maximum DR potential that the DR aggregator can either buy or sell in each period is assumed to be 10 MW. The aggregator is assumed to be a DR buyer from 2 am to 5 am and a seller from 9 am to 12 pm and 5 pm to 9 pm.

4.2. Numerical results

The given mixed integer programming approach is solved for various risk levels using CPLEX 11.1.1 under GAMS [29]. Note that hereafter the risk level \( (\rho) \) is shown by “Rho” throughout the figures.

Fig. 4 depicts the expected profit versus the standard deviation for the given risk levels. The risk-averse wind power producer \( (\rho = 2) \) obtains the expected profit of $16560 with the deviation of $7740. As the producer becomes more of a risk taker (i.e. the risk level decreases), both the expected profit and the standard deviation grow. This is more obvious for the risk-neutral wind power producer \( (\rho = 0) \), where the expected profit and its deviation are $16,713 and $8000, respectively. In other words, the risk-neutral wind power producer obtains 1% higher profit than the risk-averse one with the cost of 3.4% higher profit deviation.

Figs. 5 and 6 show the bids placed into the day-ahead market and the power exchanged in the balancing market, respectively. While the risk-neutral wind power producer places the majority of its energy offer into the day-ahead market (see Fig. 5), its offer in the balancing market is low and even negative in some periods (see Fig. 6). That is, the risk-neutral producer takes risk in some periods to bid higher than its energy production with the hope of buying that amount in the balancing market at a cheaper cost. This trend is more obvious at hours 16–18 where at each hour the wind power producer has to buy more than 5 MW from the balancing market to compensate its high offer in the day-ahead market.

Increasing the risk level leads a significant drop in the day-ahead market bids. For instance, while the producer with risk level \( \rho = 0.5 \) has a reasonable day-ahead sale share during its peak production, the shares of the most risk-averse wind power producers \( (\rho = 1.5 \) and \( \rho = 2) \) are almost negligible in the day-ahead market. Indeed, risk-averse producers sell the majority of their energy into the balancing market. This trend is reasonable since the risk-averse producers refuse to take more risk by selling their energy into the day-ahead market while their production and also the market price are associated with a significant level of uncertainty. Thus they choose the balancing market where they are close to real time and have a better forecast of their production as well as the market price.

The DR volumes obtained by the wind power producer in various risk levels are illustrated in Fig. 7. The wind power producer sells DR to the aggregator at 2–5 am and buys DR at 9 am–12 pm.
and 5–9 pm. Risk taker wind power producers have a high sale share through DR. This is particularly evident for the risk-neutral producer, where its DR sales for 3 am and 4–5 am are 5 MW and 4 MW, respectively. This share however decreases for risk-averse wind power producers. More specifically, this falling trend is significant for the risk levels $\rho = 1.5$ and $\rho = 2$ during the period 3–5 am. It can be seen that the DR sale decreases to less than 2 MW in these periods. This declining trend is sensible since risk-averse producers tend to sell the majority of their energy through the balancing market where they have a better forecast of their production as well as the market price (see Fig. 6). Hence, selling energy through DR on the day prior to the energy delivery can increase their risk as they may face power shortage in the delivery time and consequently not be able to meet the sold power through DR.

During the periods in which the wind power producer is a DR buyer, i.e. 9–12 pm and 5–9 pm, the risk-neutral producer buys more DR than the risk-averse one. It can be seen that during most hours, the risk-neutral producer buys around 2 MW DR from the aggregator. However, increasing the risk level is followed by a decreasing trend in most hours. This is more apparent at 10 am, 12, 8 and 9 pm where the share of DR procurement by risk-averse wind power producers, particularly in the risk levels $\rho = 1.5$ and $\rho = 2$ is almost negligible. This tendency is true since buying energy from DR in a fixed cost and selling it into the volatile market increases the risk of risk-averse wind power producers and hence, they may avoid this practice.

Fig. 8 delivers the DR prices offered by the wind power producer at various risk levels. In addition, DR price scenarios by other competitors (shown in Fig. 3) are also depicted in this figure to provide a better comparison. Note that competitors are indicated with “C”, while “S” represents the scenarios. The risk-neutral wind power producer offers around $1\,\text{$/MW\text{h}$ lower price than the risk-averse producers at 3–5 am. This lower price indeed resulted in a higher sale share shown in Fig. 7. For the rest of the periods in which the wind power producer buys DR from the aggregator this inclination is reversed. Actually, the risk-neutral producer offers higher prices to procure more DR as depicted in Fig. 7. For instance, this producer gives around $1.5\,\text{$/MW\text{h}$ higher than risk-averse producers at 10–11 am and 8–9 pm. In compared with the other competitors, the DR prices given by the wind power producers are low in the first period covering 2–5 am. However, for the remaining periods, wind power producers offer DR prices close to the other competitors.

4.3. Sensitivity analysis

This section evaluates the impact of power production uncertainty on the proposed strategy. A deterministic case (Case1) is compared with the current study in the paper (Case2). Indeed, the expected wind power production, shown in Fig. 2, is considered as the wind power input in the deterministic case. The day-ahead offers by the risk-neutral and risk-averse wind power producers are illustrated in Figs. 10 and 11. Further results are as follows.

Fig. 7. DR obtained by the wind power producer.

Fig. 8. The DR price offered by the wind power producer.

Fig. 9. The total DR share traded with other players and the DA market.
Both risk-neutral and risk-averse producers have no participation in the balancing market when their production is known (Case 1). The risk-neutral producer has exactly the same DR trading in both cases. However, DR trading by the risk-averse producer is different in case 1 than case 2 (See Fig. 12).

The main findings from Cases 1 and 2 are as follows.

1. As can be seen from Fig. 10, the day-ahead offer by the risk-neutral wind power producer mostly follows its expected production in Case 1, where the producer perfectly knows its production. Indeed, the differences are as a result of DR trading since the producer in Case 1 has no involvement in the balancing market. On the other hand, it is obvious that when the producer has uncertain power production, its day-ahead offer significantly changes due to that uncertainty. Actually, the producer has to compensate this deviation in the balancing market (refer to Fig. 6).

2. The interesting point is interpreted for the risk-averse wind power producer. It can be seen from Fig. 11 that the risk-averse wind power producer mostly prefers to sell through the day-ahead market if its production is perfectly known (Case 1). This is in contrast to the Case 2, where the wind power production is faced with uncertainty and thus, the risk-averse producer mainly prefers to participate in the balancing market due to its better production forecast in that market.

3. The risk-averse wind power producer sells more energy through DR in Case 1 than Case 2 (see period 1 in Fig. 12). This is reasonable since the power production in Case 1 is deterministic and therefore, the producer can hedge against the risk of the market by selling a portion of its energy through the bilateral DR contract. Note that the producer behavior in buying DR is arbitrary (periods 2 and 3 in Fig. 12). This is mainly because of two opposite aims: on one hand, the risk-averse producer is not interested in buying DR to sell it in the volatile market; on the other hand, the producer may find some periods in which buying DR is beneficial as there may be a chance of increasing its profit. This happens in period 3, where the market price is at its peak (See the expected day-ahead price in Fig. 2).

5. Conclusions

This paper presents a new energy offering plan for wind power producers. The producer is allowed to trade DR with a DR aggregator. The problem is formulated in a bilevel programming approach where the upper-level represents the wind power producer profit maximization objective and the lower-level problem models the aggregator behavior through its own revenue function. The bilevel problem is then transformed into a single-level linear programming approach through proper techniques in order to make it solvable using commercially available software.

The overall problem is a stochastic programming approach in which the risk is carried out using CVaR. A case of the Nordic Market is chosen to assess the validity of the given problem. The main findings are as follows. (1) While risk-neutral wind power producers mostly sell their energy in the day-ahead market, risk-averse

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producers mainly choose the balancing market to participate in. (2) The wind power producer can buy DR during the peak price periods to lessen the risk of its power production and market price uncertainty. On the other hand, the producer is able to sell some portion of its energy through DR contracts with the aggregator during off-peak periods. (3) While the risk-neutral wind power producer has a higher share in DR trading, either in selling or in buying, the risk-averse producers mostly refuse to be involved in DR. (4) Modelling the DR aggregator behavior makes DR trading more competitive since the wind power producer is required to compete with other players to offer a reasonable DR price to the DR aggregator. (5) The uncertainty of wind power production affects day-ahead offers of both risk-neutral and risk-averse wind power producers, particularly the latter.

Appendix A. KKT optimality conditions

To make the lower-level problem in a standard form, we can replace the maximization function by a minus minimization function. Then, the Lagrangian function of the lower-level problem is given as:

$$L = - \sum_{t \in \text{sp}} \pi(s) \cdot C^{RL}(t) \cdot \left[ \lambda^{DA}(t,s) + \lambda^{DA}(t,s) + \sum_{c = 1}^{N_c} \lambda_{sp}^{c}(t,s) \cdot \gamma^{c}(t,s) \right]$$

$$- \gamma^{c}(t,s) \cdot \left( \lambda^{DA}(t,s) + \sum_{c = 1}^{N_c} \lambda_{sp}^{c}(t,s) - 1 \right)$$

$$- \mu^{w}(t,s) \cdot \lambda^{DA}(t,s) - \mu^{DA}(t,s) \cdot \lambda^{DA}(t,s) - \mu^{c}(t,s) \cdot \lambda^{DA}(t,s) \cdot \lambda^{DA}(t,s) - \sum_{c = 1}^{N_c} \lambda_{sp}^{c}(t,s) \cdot \gamma^{c}(t,s)$$

$$\cdot \lambda^{DA}(t,s)$$

(A1)

In this function, $\gamma^{c}(t,s)$, $\mu^{w}(t,s)$, $\mu^{DA}(t,s)$ and $\mu^{c}(t,s)$ are the relevant Lagrangian multipliers of the lower-level constraints. Accordingly, KKT conditions associated with the lower-level problem are obtained as follows.

$$\frac{\partial L}{\partial \lambda^{DA}(t,s)} = - \sum_{t \in \text{sp}} \pi(s) \cdot C^{RL}(t) \cdot \gamma^{c}(t,s) - \mu^{w}(t,s) = 0$$

$$\frac{\partial L}{\partial \gamma^{c}(t,s)} = - \sum_{t \in \text{sp}} \pi(s) \cdot C^{RL}(t) \cdot \lambda^{DA}(t,s) - \mu^{DA}(t,s) = 0$$

$$\frac{\partial L}{\partial \lambda^{DA}(t,s)} = - \sum_{t \in \text{sp}} \pi(s) \cdot C^{RL}(t) \cdot \lambda^{DA}(t,s) - \mu^{c}(t,s) \cdot \gamma^{c}(t,s) = 0 \forall c = 1, \ldots, N_c$$

$$\mu^{w}(t,s), \mu^{DA}(t,s), \mu^{c}(t,s) \geq 0 \forall t, s, c$$

$$\mu^{w}(t,s) \cdot \lambda^{DA}(t,s) = 0$$

$$\mu^{DA}(t,s) \cdot \lambda^{DA}(t,s) = 0$$

$$\mu^{c}(t,s) \cdot \lambda^{DA}(t,s) = 0 \forall c = 1, \ldots, N_c$$

(A2) (A3) (A4) (A5) (A6) (A7) (A8)

Note that (A5)–(A8) are complementarity conditions. Eqs. (A6)–(A8) make the problem nonlinear. The following subsection addresses how to make these equations linear.

Appendix B. Linearizing complementarity slackness conditions

With the cost of adding some binary variables, the complementarity slackness conditions can easily be linearized as follows [25].

$$\sigma^{DA}(t,s) \leq M^{DA} \cdot v^{DA}(t,s)$$

$$\sigma^{DA}(t,s) \leq M^{DA} \cdot v^{DA}(t,s)$$

$$\sigma^{sp}(t,s) \leq M^{sp} \cdot v^{sp}(t,s) \forall c = 1, \ldots, N_c$$

$$\mu^{w}(t,s) \leq M^{w}(1 - v^{w}(t,s))$$

$$\mu^{DA}(t,s) \leq M^{DA}(1 - v^{DA}(t,s))$$

$$\mu^{c}(t,s) \leq M^{c}(1 - v^{c}(t,s)) \forall c = 1, \ldots, N_c$$

where $M^{DA}$, and $M^{w}$ are sufficiently large constants and $v^{DA}$, $v^{w}$ and $v^{c}$ are binary variables.

Appendix C. Strong duality theorem

The strong duality theorem can be used to extract the linear formulation of the product of $p^{DA}(t) \cdot \lambda^{DA}(t)$. The dual of the lower-level problem for the upper-level variable $\lambda^{DA}(t)$ is given in (A15). Note again that we replace the maximization function in the lower-level problem by a minus minimization function to have it in a standard form.

$$\max \sum_{t \in \text{sp}} \pi(s) \cdot \gamma^{c}(t,s)$$

(A15)

where $\gamma^{c}(t,s)$ is the dual variable of the lower-level equality (21). According to the strong duality theorem, the values of primal objective function (20) and the dual function (A15) must be equal at the optimal solution. That is:

$$\sum_{t \in \text{sp}} \pi(s) \cdot \gamma^{c}(t,s) = \sum_{t \in \text{sp}} \pi(s) \cdot C^{RL}(t) \cdot \left[ \lambda^{DA}(t,s) + \lambda^{DA}(t,s) + \sum_{c = 1}^{N_c} \lambda_{sp}^{c}(t,s) \cdot \gamma^{c}(t,s) \right]$$

$$- \gamma^{c}(t,s) \cdot \left( \lambda^{DA}(t,s) + \sum_{c = 1}^{N_c} \lambda_{sp}^{c}(t,s) - 1 \right)$$

$$- \mu^{w}(t,s) \cdot \lambda^{DA}(t,s) - \mu^{DA}(t,s) \cdot \lambda^{DA}(t,s) - \mu^{c}(t,s) \cdot \lambda^{DA}(t,s) \cdot \lambda^{DA}(t,s) - \sum_{c = 1}^{N_c} \lambda_{sp}^{c}(t,s) \cdot \gamma^{c}(t,s)$$

$$\cdot \lambda^{DA}(t,s)$$

(A16)

Given the above expression and also from (18), the product of $p^{DA}(t) \cdot \lambda^{DA}(t)$ is easily obtained.

$$p^{DA}(t) \cdot \lambda^{DA}(t) = \sum_{t \in \text{sp}} \pi(s) \cdot C^{RL}(t) \cdot \lambda^{DA}(t,s) \cdot \lambda^{DA}(t,s)$$

$$- \sum_{t \in \text{sp}} \pi(s) \cdot \gamma^{c}(t,s) - \sum_{t \in \text{sp}} \pi(s) \cdot \lambda^{DA}(t,s) \cdot \lambda^{DA}(t,s)$$

$$- \sum_{c = 1}^{N_c} \lambda_{sp}^{c}(t,s) \cdot \gamma^{c}(t,s)$$

(A17)

This product is now linear and can be used in the equivalent single-level objective function.

References


A new demand response scheme for electricity retailers

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ABSTRACT

A new demand response (DR) scheme from the retailers’ point of view is presented in this paper. The proposed DR scheme allows a retailer to decide how to buy DR from aggregators and consumers. Various long-term and real-time DR agreements are proposed, where they are considered as energy resources of retailers in addition to the commonly used providers. These innovative agreements include pool-order options, spike-order options, forward DR contracts and reward-based DR. A stochastic energy procurement problem for retailers is formulated, in which pool prices and customers’ participation in the reward-based DR are uncertain variables. The feasibility of the problem is assessed using a realistic case of the Queensland jurisdiction within the Australian National Electricity Market (NEM). The outcomes indicate the usefulness of the given DR scheme for retailers, particularly for the conservative ones.

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1. Introduction

1.1. Literature review, contributions and approach

Demand response (DR) can play a vital role in alleviating market and network issues. While network providers employ DR to maintain the security and reliability of the network, mitigating the risk of pool price volatilities is the main aim of using DR by electricity retailers.

There are various papers focusing on DR. The basic definitions and classifications of DR programs are addressed in [1], where DR is divided into two main categories, namely incentive and price-based programs. The elasticity concept is introduced in [2], where it reflects the responsiveness of customers to price changes. Incentive-based DR programs are formulated in some papers such as [3–5]. Ref. [3] provides the mathematical formulations of DR programs. A coupon-based method is formulated in [4], where the incentive offered to consumers is determined according to the market price. An incentive-based scheme is presented in [5], in which both the energy cost and peak-to-average ratio are minimized through a game theory approach. Price-based DR actions are presented in many research articles such as [6,7]. Authors in [6] model a real-time DR, where consumers are able to adjust their energy usage based on real-time prices. A comprehensive time-of-use is formulated in [7], where the elasticity is modeled as a non-zero cross and flexible function. Technical aspects of DR are illustrated in several papers. For instance, detailed control strategies of managing electrical loads like water heater, air conditioners, space heating and cooling systems are provided in [8–12].

A new concept is introduced in [13,14], where DR is treated as a public good. Authors in [13] devise a DR Exchange, in which buyers and sellers trade DR in a pool-based market. This market is modified in [14], where a Walrasian market clearing technique is used instead of the former pool-based method.

Option valuation theories are used to evaluate the economic value of DR. Paper [15] formulates option values for three distinct DR programs, known as load curtailment, load shifting and fuel substitution. Consequently, customers can decide whether to invest in these DR programs. This option valuation is applied to the critical peak pricing program in [16,17]. Furthermore, a stochastic programming approach is proposed in [18], where industry customers can agree whether to accept a load curtailment option.

In line with retail markets, DR is a useful resource of hedging risk by retailers. However, few papers address this concept: authors in [19] use interruptible loads to alleviate the uncertainty of pool markets faced by a load serving entity. Two interruptible load contracts, pay-in-advance and pay-as-you-go, are evaluated in [20] as the energy resources of electricity retailers. Self-production is also used in [21] to limit the risk of cost fluctuations in pool markets. Ref. [22] uses interruptible loads as an energy resource of distribution companies. A short-term deterministic model is presented in [23], in which distribution companies can use interruptible loads to place bids in the market. Besides interruptible loads, real-time pricing and time-of-use are also offered by distribution companies to alter the energy usage of consumers [24].

Concluding the above background, the following points can be stated. (1) The majority of studies on DR focus on the basic concepts,
formsulations and technical aspects of DR. To our knowledge, only authors in [13,14] investigate a mechanism through which DR is traded as a commodity between its providers and buyers. (2) Though some papers address the financial option concept, they mostly assess DR valuations from a customers’ point of view. There is no significant work investigating trading DR option contracts. (3) Less attention has been paid to the applicability of DR by electricity retailers, where among all DR, mostly the interruptible load program is considered.

Considering these highlights, the contributions of this paper are summarized as follows.

Firstly, this paper proposes a new DR scheme in which DR is treated as a public good. The proposed scheme differs from that of [13,14] in two main directions. (1) In the proposed method, DR is directly traded between its providers and buyers. (2) The proposed scheme involves various DR agreements which cover both long-term and short-term actions: A forward DR contract is proposed through which DR is traded in a certain volume and price for a given period. In addition, by adapting the well-known financial option concept [25,26], two distinct DR options are proposed here: pool-order and spike-order options. While pool-order options are useful to hedge against small deviations of pool prices, spike-order options are employed during price spikes. These DR options are mathematically formulated in this paper. Finally, a reward-based DR [27] is considered as a real-time resource in the proposed DR scheme. According to this DR, the volume of load reduction increases as higher incentives are offered by the retailer. This DR is modeled stochastically, where the unpredictable behavior of consumers is modeled through a scenario-based participation factor.

Secondly, the developed DR scheme is modeled as the energy resource of electricity retailers. This scheme allows retailers to decide how to procure various DR agreements from aggregators or large consumers. Retailers are able to purchase DR through secure contracts (forward DR). They can also set DR option agreements (pool-order and spike-order options) which their exercising depends on the pool market volatilities. Finally, they can rely on real-time DR (reward-based DR) of which its outcome is influenced by customers’ behavior.

The effectiveness of the proposed DR scheme is evaluated on an energy procurement problem, in which the retailer aims to minimize its energy cost while maintaining its desired risk level. It is assumed that the retailer employs DR in addition to forward contracts and pool markets. A stochastic programming approach is formulated, where pool prices and customer’s behavior are considered as uncertain variables. The risk is modeled by conditional value-at-risk (CVaR). The problem is analyze on a realistic case of the Queensland region within the Australian NEM.

1.2. Motivations in the Australian NEM

In Australia, several trial DR programs have been implemented by market entities such as network service providers as well as electricity retailers. Nevertheless, DR is still in its early stage in the NEM. This is derived from many challenges such as customers’ unwillingness to participate in DR, the lack of enough knowledge and training, the lack of proper metering facilities (smart metering) and market barriers such as market policies and registration fees.

The peak growth rate has become worse in the NEM over the past few years. Between 2005 and 2011, the peak growth rate was about four times higher than that of energy growth [28]. The Australian government estimated that 25% of retail electricity costs come from peak events even though they occur for a period of less than 40 h a year [28]. Note that the peak demand has been decreased from 2011 to 2012. This decrement trend is due to several factors, where global recession, high penetrations of roof-top PV and a mild summer are deemed to be the main reasons [29].
In addition, the full retail contestability in most states allows all electricity consumers to choose their retailers in the NEM. This contestability can enhance the competition in the retail market.

Considering the above motivations, more attention has recently been paid to the implementation of DR across the NEM. The Ministerial Council on Energy of Australia asked the Australian Energy Market Commission (AEMC) to facilitate efficient demand side participation (DSP) in the NEM. Consequently, the AEMC has investigated the challenges and potentials of DR in Australia in its latest report [30] and suggested promoting recommendations to facilitate DR. The AEMC has emphasized the importance of market parties' roles in assisting DR. In this way, retailers are expected to identify demand side participation opportunities, where they employ DR to lessen the risk of pool price volatility. Aggregators are also invited to play an intermediary role in buying DR from consumers to resell to other entities. For instance, EnerNOC [31] currently provides DR to TransGrid, the transmission network service provider in NSW, Australia.

According to the AEMC report, it is estimated that the reduction in the three major states of Australia (NSW, QLD and VIC) would be between 400 MW and over 1300 MW by 2020. This would lead to a cost saving of between $4.3 and $11.8 billion over the next 10 years, which equates to 3–9% of the total forecast expenditure on the supply side.

2. Comprehensive DR scheme

The proposed DR scheme for retailers is shown in Fig. 1. The retailer can set various DR contracts with aggregators or even consumers. These contracts are determined with a specific volume of DR, its price and the period in which the given contract is applied. Each contract has unique features which are discussed in this section.

It should be emphasized that though DR providers are able to sell their DR capacity through different markets such as the pool and ancillary services [32–34], this paper studies those DR aggregators intending to sell DR to retailers. In addition, it is assumed that retailers are not involved in the technical aspects of DR programs. In fact, DR providers are responsible for implementing a variety of DR programs such as interruptible load programs, critical peak pricing, peak time rebate, load shifting, priced-based DR programs and distributed generation. Each program may be valid for a short horizon (for example 30 min). However, they can together cover a longer period (for instance, several hours). A similar case exists in Australia, where TransGrid buys DR from EnerNOC [31] without concerning the details of DR programs.

![Fig. 1. The DR scheme in the energy problem of a retailer.](image)

![Fig. 2. The structure of the pool-order option.](image)

2.1. Pool-order option

A retailer can arrange a pool-order option with DR sellers. This agreement is set for a certain volume of energy and price. According to this contract the retailer has the right but not an obligation to purchase DR. This means that the retailer signs this contract at the beginning of the decision time horizon. However, exercising the contract at the energy delivery time depends on whether it is profitable or not. In other words, the contracted DR is physically traded only if the overall cost of DR is lower than the cost of buying energy from the pool. Otherwise the retailer has to pay a predetermined fee to DR sellers as the penalty of not exercising the contract. Fig. 2 shows the structure of a typical pool-order option.

The cost of pool-order options is mathematically formulated as:

\[
C(\text{PO}) = \sum_{(t, \text{po}=1)}^{N_{\text{po}}} \left[ P_{\text{po}}(t) \cdot \lambda_{\text{po}}(t) \cdot \nu_{\text{po}}(t) \cdot d(t) + (1 - \nu_{\text{po}}(t)) \cdot f^\text{pen}_{\text{po}}(t) \right]
\]

(1)

\[
0 \leq P_{\text{po}}(t) \leq P^\text{MAX}_{\text{po}}(t), \quad \forall \text{po} = 1, 2, \ldots, N_{\text{po}}
\]

(2)

\[
P^\text{total}_{\text{po}}(t) = \sum_{\text{po}=1}^{N_{\text{po}}} P_{\text{po}}(t) \cdot \nu_{\text{po}}(t)
\]

(3)

Eq. (1) represents the cost of the given pool-order options over the considered time horizon. It consists of two terms addressing the cost of practicing the pool-order option and the penalty of not exercising the agreed contract. Eq. (2) enforces the upper and lower limits for each pool-order option. Finally, the total pool-order option demand is described in (3).

2.2. Spike-order option

The NEM is faced with high price periods or even price spikes during each year. For instance, while the average pool price was $43/MWh in 2012, in the worst case of the year the price spiked as high as $2892/MWh [35].
A spike-order option agreement is proposed as a way to limit the huge cost faced by retailers during high price periods. This option is similar to the pool-order, in which the retailer has the right but not an obligation to buy DR from sellers. The difference is that spike-order options are used during price spikes. When retailers and DR sellers are setting this contract, they negotiate on a desired price, called a strike price. Taking into account the strike price, the retailer can decide whether or not to exercise the spike-order option at the delivery time. Note that similar to the pool-order option, the retailer has to pay a predetermined penalty if the contract is not exercised at the clearing time.

The cost of spike-order options is given in (4). The size of each contracted option is restricted in (5). In addition, the demand of spike-order options in period $t$ is shown in (6).

$$\text{C(SO)} = \sum_{t \in T} \sum_{so=1}^{N_{so}} [P_{so}(t) \cdot \lambda_{so}^{\text{Str}}(t) \cdot v_{so}(t) \cdot d(t) + (1 - v_{so}(t)) \cdot f_{so}^{\text{gen}}(t)] \quad \text{(4)}$$

$$0 \leq P_{so}(t) \leq P_{so}^{\text{Max}}(t), \quad \forall so = 1, 2, \ldots, N_{so} \quad \text{(5)}$$

$$p_{so}^{\text{total}}(t) = \sum_{so=1}^{N_{so}} P_{so}(t) \cdot v_{so}(t) \quad \text{(6)}$$

2.3. Forward DR

A forward contract is an agreement between the buyer and seller of an asset which is traded at a given future time for a certain price [25]. This forward contract is adapted to DR, where the retailer buys DR from aggregators or consumers for a future period. The price of forward contracts is usually determined in one of the following ways [25]:

- Over-the-Counter Market: prices are directly negotiated between the buyer and the seller of forward contracts.
- Exchange-Trade Market: this is a market where standardized contracts with given size and price are traded. The benefit of this type of trading is that prices are cleared and settled through a centralized clearing house.

Since the proposed DR provides a trading scheme between retailers and DR providers, the over-the-counter market is considered for forward DR agreements.

Forward DR contracts are offered in various blocks. The cost of this type of contract is given as:

$$\text{C(FDR)} = \sum_{t \in T} \sum_{f \in F} \sum_{b=1}^{N_{f,b}} p_{f,b}(t) \cdot \lambda_{f,b}(t) \cdot d(t) \quad \text{(7)}$$

$$0 \leq p_{f,b}(t) \leq p_{f,b}^{\text{Max}}(t) \quad \text{(8)}$$

Expressions (7) and (8) show the cost of forward contracts and the boundary size of each contract’s block respectively. Forward DR demand during period $t$ is given in (9).

$$p_{f,b}^{\text{FDR}}(t) = \sum_{f=1}^{N_{f,b}} p_{f,b}(t) \quad \text{(9)}$$

2.4. Reward-based DR

The proposed reward-based DR [27] is shown in Fig. 3.

Based on this function, the volume of load reduction increases in a stepwise trend as the retailer offers higher rewards. In addition, the uncertainty of the DR outcome is modeled using a scenario-based participation factor (PF($w, t$)). This factor ranges between [0, 1]. Zero means that customers do not respond to the reward offered in the proposed reward-based DR. As this factor increases the participation rate grows. Finally, the participation factor equal to 1 indicates that the entire reward-based DR potential is attainable. Note that each factor is identified with its own probability, where the summation of all probabilities is equal to one.

The overall reward-based DR is modeled as:

$$p_{f,b}^{\text{DR}}(t) = \sum_{w \in \Omega} \pi(w) \cdot \sum_{j=1}^{N_j} \text{PF}(w, t, \bar{F}) \cdot \bar{P}_{f,b}^{\text{DR}}(t) \cdot v_{f,b,j}(t) \quad \text{(10)}$$

$$R_{f,b}^{\text{DR}}(t) = \sum_{j=1}^{N_j} R_{f,b,j}^{\text{DR}}(t) \quad \text{(11)}$$

$$\bar{P}_{f,b}^{\text{DR}}(t) \cdot v_{f,b,j}(t) \leq R_{f,b,j}^{\text{DR}}(t) \leq \bar{R}_{f,b,j}^{\text{DR}}(t) \cdot v_{f,b,j}(t) \quad \text{(12)}$$

$$\sum_{j=1}^{N_j} v_{f,b,j}(t) = 1 \quad \text{(13)}$$

Expressions (10)-(13) represent the total reduced demand by customers as a function of the reward offered by the retailer.

Taking into account the given DR Eqs. (10)-(13), the expected DR cost over all scenarios ($w \in \Omega$) is:

$$\text{EC}^{\text{RDR}}(t) = \sum_{w \in \Omega} \pi(w) \cdot \sum_{t \in T} \left[ \sum_{j=1}^{N_j} \text{PF}(w, t, \bar{F}) \cdot \bar{P}_{f,b}^{\text{DR}}(t) \cdot R_{f,b,j}^{\text{DR}}(t) \cdot d(t) \right] \quad \text{(14)}$$

3. Wholesale market suppliers

3.1. Pool market

The retailer is able to either buy energy from or sell to the pool market. Since the pool price is uncertain it is considered as a stochastic variable. This variable is modeled through a set of scenarios which represent the possible realizations of prices. As a result,
the expected cost of the pool depends on price scenarios and is formulated as following:

$$EC(P) = \sum_{w \in \Omega} \pi(w) \cdot \sum_{t \in T} P^D(t, w) \cdot \lambda^P(t, w) \cdot d(t)$$  (15)

3.2. Forward contract

A forward contract is usually fixed in different blocks, where each block is represented in a specific size and price. These blocks are provided in a stepwise manner where the price increases as the quantity of energy grows [36].

The cost of forward contracts is given as:

$$C(F) = \sum_{t \in T} \sum_{f=1}^{NF} \sum_{b=1}^{NB} P^F_{f,b}(t) \cdot \lambda^F_{f,b}(t) \cdot d(t)$$  (16)

$$0 \leq P^F_{f,b}(t) \leq p_{\text{MAX}}^F(t)$$  (17)

Similar to other contracts, each forward agreement is also controlled by a minimum and maximum demand (17). Finally, total demand of forward contracts during period $t$ is shown in (18).

$$P^F(t) = \sum_{f=1}^{NF} \sum_{b=1}^{NB} P^F_{f,b}(t)$$  (18)

4. Problem description

4.1. Risk modeling

The retailer aims to minimize its energy cost within a certain level of the risk. The risk is evaluated using the conditional value-at-risk (CVaR) measure. This technique has some advantages compared to other methods such as value-at-risk (VaR) and mean-variance, where it is coherent and convex in stochastic programming [37]. CVaR is formulated as follows.

$$\text{Min}_{\xi, \eta} \xi + \frac{1}{1-\beta} \sum_{w \in \Omega} \eta(w) \cdot \pi(w)$$  (19)

$$\text{Cost}(w) - \xi - \eta(w) \leq 0; \quad \forall w \in \Omega$$  (20)

$$\eta(w) \geq 0; \quad \forall w \in \Omega$$  (21)

The optimal value of $\xi$ represents VaR and $\eta(w)$ is a scenario-dependent variable that is equal to the difference between the cost of scenario $w$ and VaR [21]. $\beta$ is the confidence level (0.95).

4.2. Cost function

The proposed cost function (CF) consists of the cost terms as well as the risk measure.

$$\text{Min CF} = Ec(P) + C(F) + C(PO) + C(SO) + C(FDR) + C(RDR) + \rho \cdot \text{CVaR}$$  (22)

The risk level (0–$\infty$) represents the trade-off between the expected cost and risk. A conservative retailer willing to minimize the risk chooses a large value of the risk. On the other hand, a risky retailer prefers lower costs and consequently selects a risk factor close to 0. The cost function is subject to the following constraints:

- Expressions (2), (5) and (8) as the boundary limits of pool-order, spike-order and forward DR, respectively;
- Eqs. (10)–(13), indicating the reward-based DR model;
- The forward contracts enforcement (17);
- CVaR constraints, (20) and (21);
- The energy balance equation:

$$p_{\text{eq}}(t) = p_{\text{D}}(t, w) + p_{\text{F}}(t) + p_{\text{total}}^D(t) + p_{\text{total}}^F(t) + p_{\text{D}}^R(t) + p_{\text{DR}}(t)$$  (23)

5. Case study

5.1. Decision time horizon

The proposed scheme is evaluated on the peak periods of summer and winter seasons. The time horizon is divided into 32 periods, where each period corresponds to the peak times of one week. These periods consist of 12 weeks of January–March, 17 weeks of June–September and 3 weeks of December. Note that the peak duration of summer days is from 11 am to 9 pm, while those of winter days are from 6 am–10 am to 4 pm–10 pm. Note also that the values of demand and price for each period are taken by averaging the peak times of Monday–Friday in each week. It should be noted that similar to the method in [38,39], the chosen peak periods are driven by comparing the daily load profiles of Queensland in 2012.

A new factor, called the peak-to-average-ratio (PAR) is introduced in [5]. This ratio for daily load profiles is:

$$\text{PAR} = \frac{\text{Max}L_h}{(1/24) \sum_{h=1}^{24} L_h}$$  (24)

where $L_h$ is the demand at hour $h$. This concept is used in this paper to evaluate the chosen peak periods.

First, the PAR is calculated for the annual load curve of Queensland in 2012. The peak demand in 2012 is 8706 MW and the average value is 5826 MW. Hence, the PAR is approximately equal to 1.49.

Then the PAR is calculated in a way that instead of the maximum demand in the numerator, the average of the peak demand in the chosen peak period is used. This value over the considered 32 periods is around 6654 MW. Therefore, the value of the PAR is 1.14.

It can be seen that the PAR calculated based on the chosen periods is around 24% lower than the annual PAR. Since the denominators in both calculated PARs are the same (both denominators are the average value of annual demand) it can be said that the chosen periods cover approximately the top 24% of the peak load in 2012.

Decisions on the given energy resources are made as follows. The retailer signs the long-term derivatives, i.e., forward, pool-order options, spike-order options and forward DR at the beginning of the decision horizon. Throughout the time frame, decisions on (1) the execution of pool-order and spike-order options, (2) energy procurement from the pool market and (3) the energy obtained from reward-based DR, are taken.

5.2. Data preparation and assumptions

The presented scheme is evaluated on a realistic case of the Queensland jurisdiction within the NEM in 2012. There are various retailers active in this region where the largest company provides around 50% of the total demand [40]. Thus the demand of the given retailer in this paper is assumed to be equal to 50% of the Queensland demand for each period in 2012 [35]. Recall that the demand of each period is calculated by averaging the peak periods of working days in the considered week.
The pool price is an uncertain variable which requires to be modeled stochastically. This variable is characterized using proper scenarios. Various methods have been used to characterize scenario generation. However, investigating these methods is beyond the scope of this paper. An ARIMA model is applied here. According to the literature [41], ARIMA models are not very accurate to capture the nonlinearity and volatility of price data. However, this paper considers weekly prices which obviously have a lower level of variability. Hence, it can be said that the ARIMA model provides result with acceptable accuracy in this case study. In order to prove this statement, the mean absolute percentage error (MAPE) index is calculated here, which is equal to 8.38%. Comparing this MAPE with other methods [41], it can be said that the ARIMA outcome is reasonable.

A series of pool prices of Queensland from 2006 to 2012 is used to generate price scenarios [35]. The ARIMA model with its estimated parameters is shown (25). The first term indicates the autoregressive parameters. The second term represents the variability of the price data which is for each 32 periods. The third term differentiates the process to make it stable in terms of the mean value. Logarithm function is also applied to stabilize the variance of the prices. The right hand side of the equation states the moving average parameters. \(\varepsilon(t)\) is referred to as the white noise or error term.

\[
\ln(\lambda^f(t)) = (1 + 0.7\Phi_1 - 0.03\Phi_2 - 0.055\Phi_{25}) \cdot (1 - 0.34\Phi_{32}) \cdot (1 - B^t) \\
\ln(\lambda^p(t)) = (1 + 0.086\theta_1 - 0.606\theta_2 + 0.11\theta_{13} + 0.0062\theta_{25} \\
+ 0.146\theta_{99} - 0.038\theta_{100}) \cdot \varepsilon(t)
\] (25)

The standard deviation of the error is 0.586. Using the given ARIMA model, 150 sets of price scenarios are randomly generated for each period.

In addition, the behavior of customers in reward-based DR is another source of uncertainty. For this purpose, five scenarios, ranging between 0 and 1 are randomly generated. These scenarios represent the participation factor in the reward-based cost function. Furthermore, five demand scenarios are generated to address the uncertainty of customers’ demand. These scenarios are generated using the method presented in [36]. It should be noted that the number of scenarios is derived using the method in [42]. In this way, this number makes a trade-off between the tractability of the problem and the accuracy of the results.

Forward contracts span each quarter of a year in the NEM. Therefore, three contracts (F1–F3) are considered here. F1 spans the periods of quarter 1, F2 covers the 17 weeks of winter and F3 relates to the December period. It is assumed that each forward contract involves six blocks, where each block is defined with a certain price and a maximum demand size. The forward prices of the Queensland region for each quarter of 2012 are used here [40]. Note that the maximum demand of each block in each period is 450 MW.

Four pool-order and five spike-order options are taken into account. Each agreement involves a specific volume of demand and a negotiated price. The maximum demand quantities of each pool-order and spike-order option are 50 and 75 MW, respectively. The penalty of not exercising each option by the retailer is equal to 15% of the contract cost value. This penalty depends on the size of the contracted option and also the period in which the given option is set.

It is assumed that each forward DR contract is signed for a period of one month. Hence, eight forward DR agreements are provided covering eight given months of the planning horizon. Similar to forward contracts, each forward DR involves six blocks where the maximum contracted demand for each block is 75 MW.

With regards to the reward-based DR, 21 successive steps are considered in the presented stepwise function. The total potential of the given DR scheme is around 30% of the entire demand. This potential is derived based on the trial DR potential carried out in Australia [28]. Figs. 4–6 and Tables 1 and 2 illustrate the aforementioned input data.

5.3. Numerical results and discussions

The given problem is mixed-integer linear programming, which is solved using CPLEX 11.1.1 under GAMS [43].

The expected cost vs. standard deviation for various risk levels is shown in Fig. 7. While a risky retailer \((\rho = 0)\) spends around $4.72 million, the energy cost of the most conservative retailer \((\rho = 5)\) is $5.3 million. On the other hand, the values of standard deviation for the risky and conservative retailers are approximately $2.08

### Table 1

<table>
<thead>
<tr>
<th>Forward prices ($/MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>B1</td>
</tr>
<tr>
<td>----</td>
</tr>
<tr>
<td>F1</td>
</tr>
<tr>
<td>F2</td>
</tr>
<tr>
<td>F3</td>
</tr>
</tbody>
</table>
million and $333,000, respectively. This means that the risk-neutral retailer obtains an 11% reduction in the expected cost compared to the conservative one. However, this retailer expects about 83% higher cost deviation. In other words, risky retailers are expected to buy their energy at lower costs while facing much higher cost fluctuations.

Fig. 8 depicts the share of each resource in the total required energy by the retailer. The significant results are:

- As the risk factor increases the share of DR resources grows. This is more obvious from $\rho = 0$ to $\rho = 0.2$, where the DR share becomes over than twice. For larger risk levels by $\rho = 5$ the DR contribution slightly increases to around 25%. This increment rate illustrates that the proposed DR agreements are more beneficial to conservative retailers than risky ones. This is reasonable since the given DR, particularly the long-term agreements are reliable resources.
- As the pool market is a volatile resource, its energy share significantly drops once the risk factor rises. This trend is reversed for forward contracts.

Table 3 provides the percentage of each DR resource in the energy share of the retailer. As the retailer becomes more conservative, the share of all DR programs increases. This increment is significant in forward DR, where the DR share is around 4% higher for the most risk-averse retailer to around 14% for the risk-neutral one, i.e. 10% increment. The growth rate of pool-order and spike order options as well as reward-based DR is around 2%.

Figs. 9 and 10 provide the percentage of each resource in summer and winter seasons respectively. The main points interpreted from these figures are:

- Though the proportions of DR resources in summer and winter increase, as the retailer becomes more risk averse, this growth rate is higher in summer than winter. For instance, for $\rho = 5$ DR programs account for around 26% of the summer share compared to 23% of winter energy. Additionally, it can be seen that more pool-order and spike-order options are exercised in summer than in winter.
- Conservative retailers prefer to sell energy to the pool in winter. This is more obvious from $\rho = 0.2$ to $\rho = 0.5$, where the sold energy to the pool market becomes almost double.
Table 4
Exercised periods of pool-order options.

<table>
<thead>
<tr>
<th>Rho</th>
<th>PO1</th>
<th>PO2</th>
<th>PO3</th>
<th>PO4</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1–32</td>
<td>1–32</td>
<td>NE</td>
<td>NE</td>
</tr>
<tr>
<td>0.2</td>
<td>1–32</td>
<td>1–32</td>
<td>5, 7, 10, 21, 24–32</td>
<td>NE</td>
</tr>
<tr>
<td>0.5</td>
<td>1–32</td>
<td>1–32</td>
<td>1–3, 5–8, 10, 11, 17–32</td>
<td>NE</td>
</tr>
<tr>
<td>0.7</td>
<td>1–32</td>
<td>1–32</td>
<td>1–8, 10, 11, 13, 17–32</td>
<td>5, 7, 26, 30</td>
</tr>
<tr>
<td>1</td>
<td>1–32</td>
<td>1–32</td>
<td>1–11, 13, 17–32</td>
<td>5–8, 10, 11, 30, 32</td>
</tr>
<tr>
<td>5</td>
<td>1–32</td>
<td>1–32</td>
<td>1–13, 17–21, 23–26, 28–32</td>
<td>1–3, 5–8, 10, 11, 30, 32</td>
</tr>
</tbody>
</table>

Table 5
Exercised periods of spike-order options.

<table>
<thead>
<tr>
<th>Rho</th>
<th>SO1</th>
<th>SO2</th>
<th>SO3</th>
<th>SO4</th>
<th>SO5</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1–32</td>
<td>NE</td>
<td>NE</td>
<td>NE</td>
<td>NE</td>
</tr>
<tr>
<td>0.2</td>
<td>1–32</td>
<td>5, 7, 10, 11</td>
<td>NE</td>
<td>NE</td>
<td>NE</td>
</tr>
<tr>
<td>0.5</td>
<td>1–32</td>
<td>1–13, 19, 20, 24, 28, 29</td>
<td>5, 7</td>
<td>NE</td>
<td>NE</td>
</tr>
<tr>
<td>0.7</td>
<td>1–32</td>
<td>1–13, 19, 20, 23, 24, 29</td>
<td>5, 7, 11</td>
<td>NE</td>
<td>NE</td>
</tr>
<tr>
<td>1</td>
<td>1–32</td>
<td>1–13, 15, 17, 19, 20, 23, 24, 29</td>
<td>5, 7</td>
<td>NE</td>
<td>NE</td>
</tr>
<tr>
<td>5</td>
<td>1–32</td>
<td>1–15, 17, 19, 20, 24, 29</td>
<td>5–8, 10, 11</td>
<td>7</td>
<td>NE</td>
</tr>
</tbody>
</table>

Fig. 9. The percentage of energy procured from each resource in summer.

Tables 4 and 5 respectively represent the periods in which pool-order (PO) and spike-order (SO) options are exercised.

From Table 4 it can be seen that a risky retailer only exercises PO1 and PO2. For $\rho = 0.2$, PO3 is also applied, where for higher values of the risk PO4 is also instructed in some periods. Similar to pool-order options, more spike-order options are utilized once the risk level increases. The risk-neutral retailer uses only SO1. For $\rho = 0.2$, SO2 is also applied in some periods. SO3 is exercised for the risk value of 0.5 and higher than that. SO4 is practiced for $\rho = 1$ and $\rho = 5$. Note that SO5 is not used in this case.

6. Conclusions

This paper presents a new DR scheme for electricity retailers. Various long-term and real-time DR contracts including pool-order options, spike-order options, forward DR and reward-based DR are proposed. These resources are applied by energy suppliers of the retailer in addition to the forward contracts and pool markets. A stochastic energy procurement problem is formulated where pool prices and customers’ enrollment in the reward-based DR are uncertain variables. The proposed scheme is evaluated on a realistic case of the Australian NEM for different risk levels. The main outcomes are as follows:

- The case study shows the feasibility of the proposed DR scheme for retailers. The scheme allows retailers to procure their energy from various DR contracts.
- Depending on the risk level, retailers change their energy share from the proposed DR agreements. The risk-neutral retailer obtains around 10% of its energy from the given DR agreements. This share for the most conservative retailer ($\rho = 5$) increases to around 25%. Forward DR agreements play a significant role in this increment with about 10% growth.
- The DR scheme is employed in summer and winter. However, the rate of summer is higher than that of winter. This higher percentage is mostly due to the increasing usage of DR options.

References

Employing demand response in energy procurement plans of electricity retailers

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ABSTRACT

This paper proposes a new framework in which demand response (DR) is incorporated as an energy resource of electricity retailers in addition to the commonly used forward contracts and pool markets. In this way, a stepwise reward-based DR is proposed as a real-time resource of the retailer. In addition, the unpredictable behavior of customers participating in the proposed reward-based DR is modeled through a scenario-based participation factor. The overall problem is formulated as a stochastic optimization approach in which pool prices and customers’ participation in DR are uncertain variables. The feasibility of the problem is evaluated on a realistic case of the Australian National Electricity Market (NEM) and solved using General Algebraic Modeling System (GAMS) software.

Introduction

Demand Response (DR) is defined as changes in electricity usages of consumers as a response to new price tariffs and/or offered incentives [1]. Many studies have been presented to explore the basic concepts, classifications, and technical aspects of DR. The definition of DR programs are addressed in [1]. Additionally, this reference introduces various DR programs and categorizes them into two groups, namely incentive- and price-based DR. Incentive-based DR programs are formulated in several papers such as [2–4]. Ref. [2] provides the mathematical formulations of interruptible load services. A coupon-based method is formulated in [3] where the incentive offered to consumers is determined according to market prices. An incentive-based scheme is presented in [4] through which both the energy cost and peak-to-average ratio are minimized using a game theory approach. Price-based DR actions are also presented in many researches such as [5–8]. Paper [5] models a real-time pricing approach for smart grid applications. Authors in [6] address the elasticity concept which reflects the responsiveness of customers to price changes. A comprehensive time-of-use model is formulated in [7] where the elasticity is considered as a non-zero cross and flexible function. A commercial DR concept is introduced in [8] in order to study DR impacts on the power market. Finally, the detailed control strategies of managing electrical loads such as water heater systems, air conditioners, space heating and cooling systems are provided in [9–13].

Electricity retailers are intermediary companies which buy electricity from wholesale markets and resell it to consumers. They procure the required energy mainly from pool markets and bilateral contracts. Another useful energy resource which can be employed by retailers is DR. However, a few studies in the literature address this concept. Authors in [14] use interruptible loads to alleviate the uncertainty of pool markets faced by a load serving entity. Two interruptible load contracts, pay-in-advance and pay-as-you-go, are evaluated in [15] as suppliers of retailers. Self-production is also used in [16] to limit the risk of cost fluctuations in pool markets. Ref. [17] uses interruptible loads as an energy resource of distribution companies. A short-term deterministic model is presented in [18] where distribution companies can use interruptible loads to bid into the market. Authors in [19] use interruptible programs in short-term decisions of retailers. Besides interruptible loads, real-time pricing and time-of-use are also offered by retailer to alter the electricity usage of consumers [20].

This paper proposes a stepwise reward-based DR in which the uncertainty of customers’ behavior is modeled through a scenario-based participation factor. A medium-term energy procurement framework is proposed for retailers in which they employ the reward-based DR in addition to forward contracts and a pool market. A stochastic programming approach is formulated where both pool prices and customers’ behavior are considered as uncertain variables. The overall problem is mixed-integer...
The proposed reward-based DR is illustrated in Fig. 1. According to this function, offering higher rewards by the retailer is followed by a stepwise growth in the expected reduced load by customers.

In addition, the uncertainty of DR outcomes is modeled through a scenario-based participation factor \( PF(w, t) \). This factor ranges between [0,1]. Zero means that customers are not willing to participate in the reward-based DR. However, as the participation factor increases, the participation rate grows, where ultimately the participation factor equal to 1 indicates that the entire reward-based DR potential is attainable.

The overall reward-based DR is derived from Fig. 1 as follows:

\[
R_{DR}(t) = \sum_{i=1}^{N_s} R_{DR,i}(t) \sum_{j=1}^{N_f} P_{DR,i}(t) \cdot \nu_{DR,j}(t)
\]

(1)

\[
R_{DR,j}(t) = \sum_{j=1}^{N_f} P_{DR,j}(t)
\]

(2)

\[
R_{DR,j}(t) \cdot \nu_{DR,j}(t) \leq R_{DR,j}(t) \leq R_{DR,j}(t) \cdot \nu_{DR,j}(t)
\]

(3)

Expression (1) indicates the volume of load reduction \( P_{DR}(t) \) as the product of participation scenarios \( PF(w, t) \) and the reduced load level shown in Fig. 1 \( P_{DR}(t) \). Eq. (2) states the reward offered to customers. Constraint (3) binds the reward of each interval as shown in Fig. 1. Eq. (4) enforces that only one interval of the reward-based DR curve can be chosen.

### Problem description

This paper delivers a medium-term planning horizon for procuring energy by a retailer during high-price periods (Fig. 2). At the beginning of the time horizon, the retailer decides proper forward contracts. Note that the share of forward contracts is decided under the uncertainty of pool prices and customers’ behavior. Throughout the time frame, the amount of energy to be bought/sold from/to the pool market as well as the energy volume obtained from DR is set.

### Proposed framework

#### Reward-based DR

The proposed reward-based DR is illustrated in Fig. 1. According to this function, offering higher rewards by the retailer is followed by a stepwise growth in the expected reduced load by customers.

In addition, the uncertainty of DR outcomes is modeled through a scenario-based participation factor \( PF(w, t) \). This factor ranges between [0,1]. Zero means that customers are not willing to participate in the reward-based DR. However, as the participation factor increases, the participation rate grows, where ultimately the participation factor equal to 1 indicates that the entire reward-based DR potential is attainable.

The overall reward-based DR is derived from Fig. 1 as follows:

\[
P_{DR}(t) = \sum_{w=1}^{N_s} \sum_{j=1}^{N_f} PF(w, t) \cdot P_{DR,j}(t) \cdot \nu_{DR,j}(t)
\]

(1)

\[
P_{DR,j}(t) = \sum_{j=1}^{N_f} P_{DR,j}(t)
\]

(2)

\[
P_{DR,j}(t) \cdot \nu_{DR,j}(t) \leq P_{DR,j}(t) \leq P_{DR,j}(t) \cdot \nu_{DR,j}(t)
\]

(3)

Expression (1) indicates the volume of load reduction \( P_{DR}(t) \) as the product of participation scenarios \( PF(w, t) \) and the reduced load level shown in Fig. 1 \( P_{DR}(t) \). Eq. (2) states the reward offered to customers. Constraint (3) binds the reward of each interval as shown in Fig. 1. Eq. (4) enforces that only one interval of the reward-based DR curve can be chosen.
The proposed decision making problem is associated with the uncertainties of pool prices and customers’ behavior participating in the reward-based DR. To represent possible realizations of these stochastic variables, a scenario tree is constructed, (Fig. 3). The root node corresponds to the point at which the share of forward contracts is determined. Branches leaving this node represent different realizations of pool price scenarios. Hence, decisions on the pool market are made in stage two. Finally, for each pool price, a set of scenarios representing the uncertainty of the customers’ behavior is generated. Consequently, the DR outcome is obtained in the third stage.

Mathematical formulation

The objective function consists of the following terms.

Expected revenue

The expected revenue from selling energy to consumers is calculated as follows.

\[
ER = \sum_{w=1}^{N_s} \pi(w) \cdot \sum_{i=1}^{T} \sum_{j=1}^{N_I} P_i^F(w, t) \cdot X_i^j(t) \cdot d(t)
\]  

(5)

where \( P_i^F(w, t) \) and \( X_i^j(t) \) are illustrated in the price-quota curve (Fig. 4) [21]. They, respectively, indicate the sold power to consumers and its price. \( T \) is the number of periods in the considered time horizon. Note that a bilevel programming approach has also been proposed in [22] as an alternative method to the presented price-quota curve. However, for the sake of simplicity and without loss of generality, we use the price-quota curve concept in our problem.

According to this curve, the demand supplied by the retailer is modeled as:

\[
P^F(w, t) = \sum_{i=1}^{N_s} \pi(w) \cdot \sum_{j=1}^{N_I} P_i^F(w, t) \cdot X_i^j(t) \cdot d(t)
\]  

(6)

\[
\lambda_i^j(t) = \sum_{i=1}^{N_s} \lambda_i^j(t) \leq \lambda_i^j(t) \cdot v_i(t)
\]  

(7)

\[
\lambda_i^j(t) \cdot v_i(t) \leq \lambda_i^j(t) \cdot v_i(t)
\]  

(8)

\[
\sum_{i=1}^{N_s} v_i(t) = 1
\]  

(9)

Eqs. (6)–(9) formulate the price-quota curve shown in Fig. 4.

Expected cost of DR

Based on the proposed reward-based DR in section ‘Reward-based DR’, the expected cost of DR is formulated as (10).

\[
EC(\text{DR}) = \sum_{w=1}^{N_s} \pi(w) \cdot \sum_{i=1}^{T} \sum_{j=1}^{N_I} P_i^F(w, t) \cdot P_i^{\text{DR}}(t) \cdot \lambda_i^j(t) \cdot d(t)
\]  

(10)

Expected revenue/cost of pool market

The retailer can either purchase energy from or sell it to the pool market. The expected revenue/cost of the pool market is given in (11).

\[
EC(\text{pool}) = \sum_{w=1}^{N_s} \pi(w) \cdot \sum_{i=1}^{T} P_i^F(w, t) \cdot \lambda_i^j(w, t) \cdot d(t)
\]  

(11)

\[
P_i^F(w, t) \text{ and } \lambda_i^j(w, t) \text{ are the power traded in the pool and the pool price of scenario } w \text{ during time period } t, \text{ respectively.}
\]

Forward contracts cost

A forward contract is usually fixed in different contract blocks, where each block is represented in a specific size and price. These blocks are provided in a stepwise manner, where the price increases as the quantity of energy grows. The cost of forward contracts is given in (12). Also, the size of each contract block is enforced in (13).

\[
EC(\text{forward}) = \sum_{i=1}^{T} \sum_{f=1}^{N_s} \sum_{j=1}^{N_I} P_i^F(t) \cdot X_i^j(t) \cdot d(t)
\]  

(12)

\[
0 \leq P_i^F(t) \leq P_i^\text{max}(t)
\]  

(13)

Risk measure

Different techniques have been used to model the risk measure in financial problems. However, conditional value-at-risk (CVaR) takes some advantages than other methods such as value-at-risk
CVaR is defined as the expected profit not exceeding VaR [22]:

$$\text{CVaR} = \mathbb{E}(\text{profit}|\text{profit} \leq \text{VaR})$$

where

$$\text{VaR} = \max\{x|\mathbb{P}(\text{profit} \leq x) \leq 1 - \beta\}$$

where $\beta$ represents the confidence level, which is usually taken as 0.95 [21]. Therefore, CVaR is formulated as:

$$\max_{f(x|w), \xi} \frac{1}{1 - \beta} \sum_{w=1}^{N_s} \eta(w) \cdot \pi(w)$$

subject to

$$-\text{profit}(w) + \xi - \eta(w) \leq 0, \quad \forall w = 1, 2, \ldots, N_s$$

$$\eta(w) \geq 0, \quad \forall w = 1, 2, \ldots, N_s$$

Constraints (17) and (18) are used to linearize the CVaR measure. $\text{profit}(w)$ is the profit obtained in scenario $w$. The optimal value of $\xi$ represents the VaR, and $\eta(w)$ is a scenario-dependent variable that is equal to the difference between the VaR and the profit of scenario $w$ [21].

### Overall objective function

The overall profit function is given in (19). The first three terms are dependent on scenarios. Hence, they are averaged over all scenarios. The first term indicates the revenue obtained from selling energy to customers. The second term gives the cost of the pool market, while the third term denotes the cost of reward-based DR. The fourth term is the cost of forward contracts, which is independent of scenarios. Finally, the last term illustrates the CVaR risk measure which is weighted using the risk factor ($\rho$). The risk level ($[0, \infty)$) instead represents the trade-off between the expected cost and the risk. A conservative (risk-averse) retailer willing to minimize the risk chooses a large value of risk. On the other hand, a risk-neutral retailer prefers lower costs and consequently selects a risk factor close to 0.

$$\text{Maximize} \sum_{w=1}^{N_s} \pi(w) = \sum_{w=1}^{N_s} q^w P^w(t) \cdot \xi^w(t) - P^w(t) \cdot \lambda^w(t)$$

$$- \sum_{j=1}^{N_f} P^f(j, t) \cdot \lambda^f(t) \cdot \sum_{i=1}^{N_s} \eta_i^t \cdot \pi_i^t) \cdot d(t)$$

$$+ \rho \cdot \left( 1 - \frac{1}{1 - \beta} \sum_{w=1}^{N_s} \eta(w) \cdot \pi(w) \right)$$

The profit function is subject to the following constraints:

- Eqs. (1)–(4), as DR constraints;
- Constraints (6)–(9), representing the expected revenue from selling electricity to consumers;
- Forward contracts boundary limitation, Eq. (13);
- CVaR constraints (17), (18);
- Energy balance equation as (20). This constraint enforces that the energy sold to consumers must be equal to the energy procured from the pool market as well as the reward-based DR and forward contracts.

### Case study

#### Data

The performance of the proposed method is evaluated on a realistic case of the Queensland jurisdiction within the Australian national electricity market [24]. As the proposed methodology focuses on utilizing DR resources during high-price periods, a period of 3 h in a peak day of Queensland is chosen. Note that the proposed method is also applicable for multi-period problems. Price and DR scenarios are simply generated as follows. First, 25 pool price scenarios are generated for each hour using the Autoregressive Integrated Moving Average (ARIMA) model. In order to estimate the parameters of the ARIMA model, a set of time series of Queensland market prices for 1 month spanning January 2011 is used. Secondly, for each generated pool price, four scenarios, representing different realizations of customers’ behavior, are randomly generated. The values of these scenarios range between zero and one, where zero represents no participation and ultimately, one indicates that the retailer can achieve its total expected load reduction from DR.

A percentage of the Queensland peak load is incorporated as the required demand by the retailer (Table 1). For the sake of simplicity, it is considered that the retailer has the ability to forecast its demand precisely, and hence, we assume that the retailer’s demand is known.

Three blocks of forward contracts are given. Table 2 shows the upper limit of each block’s demand and price.

#### Numerical results

The proposed problem is formulated in mixed-integer linear programming and solved using CPLEX under GAMS [25]. Fig. 7 shows the expected profit of the retailer versus the standard deviation for different risk values ($\rho$). It is obvious that as the retailer becomes more of a risk taker, both the expected profit and its standard deviation grow. However, the increment rate of the profit deviation is much higher than that of the expected profit. For example, the expected profit of a risk-averse retailer ($\rho = 20$) is around $71,000, while its standard deviation is about $6000. These values for the risk-neutral retailer ($\rho = 0$) are approximately $103,000 and $85,000, respectively. That is, the risk-neutral retailer expects to obtain 31% higher profit than the risk-averse one. However, this extra profit is achieved at the cost of expecting 93% higher profit deviation.

### Table 1

<table>
<thead>
<tr>
<th>Time</th>
<th>11 am</th>
<th>12 pm</th>
<th>1 pm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demand (MW)</td>
<td>3500</td>
<td>4245</td>
<td>3000</td>
</tr>
</tbody>
</table>

### Table 2

<table>
<thead>
<tr>
<th>Forward block</th>
<th>Maximum power (MW)</th>
<th>Price ($/MW h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>350</td>
<td>106</td>
</tr>
<tr>
<td>2</td>
<td>350</td>
<td>107</td>
</tr>
<tr>
<td>3</td>
<td>350</td>
<td>108</td>
</tr>
</tbody>
</table>
Fig. 8 represents the amounts of energy procured from DR for different risk levels. The risk-neutral retailer ($\rho = 0$) buys 351 MW h from DR, the moderate one ($\rho = 5$) obtains 277 MW h, and the risk-averse retailer ($\rho = 20$) purchases 257 MW h from DR. This falling trend is reasonable since risk-averse retailers prefer to decrease their energy share from uncertain resources (i.e. reward-based DR in our case).

The offered reward and the load reduction obtained from implementing the reward-based DR are illustrated in Table 3. It can be seen that the retailer offers various rewards depending on the time and the risk level. The rewards offered at 12 pm are higher than other hours. In addition, the risk-neutral retailer pays more rewards to customers than does the risk-averse one. For instance, the risk-neutral retailer offers $59/\text{MW h}$ at 11 am and the equal reward of $59/\text{MW h}$ at 12 pm and 1 pm. However, the rewards paid by the risk-averse retailer ($\rho = 20$) reduce to $51/\text{MW h}$ (at 11 am), $55/\text{MW h}$ (at noon) and $55/\text{MW h}$ (at 1 pm).

Table 4 represents the energy volume served by each resource for the given risk levels. As can be seen, the risk-neutral retailer prefers to buy its whole energy from the pool market and DR, where their proportions are about 93% and 7%, respectively. Hence, no forward contract is signed for $\rho = 0$. This is because of the higher
cost of forward contracts in comparing with the pool market and DR. However, higher risk values lead to a decrease in the share of the pool market and DR, and conversely an increase in the forward contribution. Once the risk level increases to 0.7, contract 1 and a portion of contract 2 are signed. For the risk level equal to 1, contract 3 is also set. Finally, the risk-averse retailer ($\rho = 20$) purchases 2679 MW h from forward contracts, which is about 70% of its total required energy.

Conclusions

This paper proposes a new framework to incorporate demand response in energy procurement problems of retailers during high-price periods. A reward-based DR is developed in which the uncertain behavior of customers is modeled through a scenario-based participation factor. The proposed problem is formulated in a stochastic programming approach and evaluated on a realistic case of the Australian NEM. The main outcomes are as follows.

1. The results show the validity of employing DR by electricity retailers, where they can rely on DR as a useful energy resource.

2. Particularly, the proposed reward-based DR is more beneficial to risk-neutral retailers, where their main preference is to increase the obtained profit. Consequently, these retailers are willing to pay higher rewards than risk-averse retailers.

3. Risk-neutral retailers expect higher profit with the cost of much higher profit deviation. This is vice versa for conservative retailers, where they seek lower risks and therefore rely more on forward contracts.

References

Developing a Scenario-Based Demand Response for Short-Term Decisions of Electricity Retailers

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Abstract— This paper deals with short-term decisions made by electricity retailers. It is assumed that a retailer aims to minimize the cost of procuring energy from two sources: one is the commonly-used pool market, and the other is the demand response (DR) program proposed in this paper. A reward-based DR is mathematically formulated where the volume of load reduction is modeled as a stepwise function of offered incentives by the retailer. Furthermore, a novel scenario-based participation factor is developed here to take into account the unpredictable behavior of customers. The presented problem is formulated in stochastic programming where its feasibility is evaluated on a realistic case of the Queensland region within the Australian National Electricity Market (NEM). Additionally, we define four distinct cases to study the impact of uncertainties associated with both resources, particularly DR, on short-term decisions of the retailer.

Index Terms— Demand response, electricity retailer, pool market, reward-based DR, scenario-based participation factor

I. NOMENCLATURE

A. Constants

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>d(t)</td>
<td>Duration of period t</td>
</tr>
<tr>
<td>P_j^DR(t)</td>
<td>Maximum load reduction of interval j</td>
</tr>
<tr>
<td>PREQ(t)</td>
<td>Total required load in period t</td>
</tr>
<tr>
<td>PF(w', t)</td>
<td>Participation factor of scenario w'</td>
</tr>
<tr>
<td>R^DR_j</td>
<td>Upper bound of the offered reward of interval j</td>
</tr>
<tr>
<td>\rho</td>
<td>Risk factor</td>
</tr>
<tr>
<td>\beta</td>
<td>Confidence level</td>
</tr>
<tr>
<td>\lambda^P(t, w'')</td>
<td>Pool price of scenario w'' in period t</td>
</tr>
<tr>
<td>\pi(w')</td>
<td>Probability of DR scenario w'</td>
</tr>
<tr>
<td>\pi(w'')</td>
<td>Probability of pool scenario w''</td>
</tr>
<tr>
<td>\pi(w)</td>
<td>Probability of scenario w as: \pi(w') \times \pi(w'')</td>
</tr>
</tbody>
</table>

B. Variables

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>P^P(t, w'')</td>
<td>Power bought from the pool in scenario w''</td>
</tr>
<tr>
<td>P^DR(t)</td>
<td>Power bought from DR</td>
</tr>
<tr>
<td>R_j^DR(t)</td>
<td>Reward of interval j</td>
</tr>
<tr>
<td>R^DR(t)</td>
<td>Offered reward t</td>
</tr>
<tr>
<td>v_{DR,j}(t)</td>
<td>Binary variable indicating level of reduced load</td>
</tr>
</tbody>
</table>

II. INTRODUCTION

A. Basic Concepts and Motivation

Demand Response is defined as modifying the load profiles of customers via offering incentives or establishing new price tariffs [1]. The key drivers of these programs comprise network and market issues. While maintaining the security and reliability of the network is the primary goal of network-driven DR, alleviating the risk of pool price volatility is known as the main cause of employing market-driven programs [2].

Among all market players, electricity retailers are the principal employers of market-driven DR, where their leading aim is to hedge against pool price fluctuations. They use DR programs ranging from long-term contracts like interruptible load contracts to real-time ones such as emergency DR. While such long-term contracts are usually set with a certain volume of load reduction, the outcome of short-term DR is uncertain due to the unpredictable behavior of customers. This uncertainty, however, may mislead retailers in which the volume of achieved load reduction can significantly violate from that of anticipated.

B. Aim and Approach

This paper aims to assess the impact of the uncertainty associated with real-time DR on short-term decisions of electricity retailers. A retailer is supposed to minimize its cost of buying the required energy from a pool market and real-time DR on an-hour-ahead basis. For this purpose, a reward-based DR is mathematically formulated. In this order, the amount of load reduction is modeled as a stepwise function of offered rewards by the retailer. Both pool prices and customers’ behavior are assumed to involve uncertainty. Proper pool price scenarios are generated using the historical data of the Queensland region within the Australian National electricity Market (NEM). In addition, a scenario-based participation factor is proposed to model the uncertainty associated with customers’ enrolling in DR. This factor ranges [0,1]. While zero means no willingness of participating in DR,
the participation rate rises by increasing this factor. Finally, the participation factor equal to 1 indicates that the entire DR potential is attainable.

C. Literature Review and Contributions

In line with incorporating DR in energy problems of retailers or other energy providers, surprisingly few studies have been investigated. Authors in [3] have applied interruptible loads (IL) to alleviate the uncertainty of pool markets faced by a load serving entity (LSE). It has been shown that ILs are of particular interest during price spikes. Self-production has also been used in [4, 5] to limit the risk of cost fluctuations of pool markets. Distributed generation and interruptible loads have been used in [6, 7] as two energy suppliers of distribution companies (DISCOs).

With regard to DR models, there have been several ongoing investigations focusing on the mathematical formulation of DR. Different DR programs have been mathematically modeled using single or multi-period economic models [8]-[12]. These models are based on an elasticity factor, defined as demand sensitivity to price changes. A new DR model has also been proposed in [13] addressing customers’ response to hourly electricity prices in which customers can adjust their consumption based on the market price. In addition, authors in [14] have proposed a new incentive-based DR using coupon rewards, where LSEs can use this scheme during peak periods to alleviate high prices.

Considering the above studies, it can be concluded that: 1) only long-term DRs such as interruptible loads have been employed as energy resources of retailers; 2) All DR models presented in the aforementioned work are formulated deterministically. These two points are addressed as the contributions of this paper. Firstly, a real-time DR is proposed to be considered in short-term decisions of retailers. Secondly, we model the presented DR in a stochastic manner to take into account the uncertainty of customers’ behavior.

D. DR Experience in the NEM

The NEM has faced several price spikes each year. For instance, the numbers of spikes higher than $5000 in 2009-10 and 2010-11 were around 95 and 40, respectively [15]. These events were mainly caused by high demand, market power, and rebidding of generation companies [15]. Among them, high peak demand is known as the key driver, where it has been the trigger of around 61% of events happened since 2008. Knowing these fluctuations, there has been the trigger of around 61% of events happened since 2008. Knowing these fluctuations, there has being an increase in the number of peak pricing (CPP) of around 38 cents/kWh. Endeavour Energy also gained 30-40% reduction for CPP of about $1.67/kWh in the Western Sydney Pricing Trial (WSPT). In a trial time-of-use tariff by Ausgrid for residential consumers, load was shifted around 4% in the normalized maximum demand. Endeavour energy implemented a peak time rebate before the 2010-11 summer and gained peak demand reduction between 29% and 51%. As an outcome of emergency DR, peak demand reduced around 265 MW in the New South Wales jurisdiction on 10 August 2010, when the price reached $6,200/MWh.

E. Paper Organization

The rest of the paper is organized as follows. Section III addresses the proposed reward-based DR. Then, the problem formulation is described in section IV. Section V covers the case study and experimental results and finally, section VI concludes the paper.

III. REWARD-BASED DR

In order to model the proposed reward-based DR, a stepwise function is developed, as shown in Fig. 1. Based on this function, the volume of load reduction increases in a stepwise trend as the retailer offers higher rewards.

![Figure 1. Reward-based DR curve](image)

In addition, the uncertainty of DR outcomes is modeled using \( PF(w', t) \) as the given scenario-based participation factor. As mentioned before, this factor ranges between 0 and 1 for different scenarios, \( w'_{1}, \ldots, w'_{N} \). The overall reward-based DR is formulated as follows:

\[
p^{DR}(t) = \sum_{w} w^{DR}, \sum_{i=1}^{N_{j}} PF(w', t). R^{DR}_{j}(t), v_{DR,j}(t) \tag{1}
\]

\[
R^{DR}_{j}(t) = \sum_{j=1}^{N_{j}} R^{DR}_{j}(t) \tag{2}
\]

\[
R^{DR}_{j-1}(t), v_{DR,j}(t) \leq R^{DR}_{j}(t) \leq R^{DR}_{j}(t), v_{DR,j}(t) \tag{3}
\]

\[
\sum_{j=1}^{N_{j}} v_{DR,j}(t) = 1 \tag{4}
\]

Expressions (1)-(4) represent the total reduced demand by customers as a function of the reward offered by the retailer. \( p^{DR}(t) \) refers to the total reduced load through implementing DR, and \( R^{DR}(t) \) indicates the reward paid to DR participants. Furthermore, \( v_{DR,j}(t) \) is a binary variable showing the level of the reduced load in the DR curve.

IV. PROBLEM FORMULATION

The proposed cost function consists of the below terms:

\[
CF = \text{Expected cost of the pool} + \text{Expected cost of DR} + \text{Risk measure}
\]

These components are described in details as follows.
• Expected cost of the pool market

As noted earlier, pool prices are uncertain where they are modeled using proper scenarios. Therefore, the expected cost of purchasing energy from the pool market is determined as the overall expectation of all scenarios’ costs. This is computed by the product of the probability of each pool price scenario \( \pi(w') \) and the cost of that scenario:

\[
EC(\text{pool}) = \sum_{w'} \pi(w') \sum_{t \in T} P^P(t, w') \lambda^P(t, w') \cdot d(t)
\]  

(5)

• Expected cost of DR

Taking into account the given DR expressions (1)-(4), the expected DR cost is formulated as follows:

\[
EC(\text{DR}) = \sum_w \pi(w') \sum_{t \in T} \left[ \sum_{j \in J} P^F(w', t) \tilde{P}^D_j(t) R^D_j(t) \cdot d(t) \right]
\]  

(6)

• Risk measure

Different techniques have been used to model the risk measure in financial problems. However, conditional value-at-risk (CVaR) takes some advantages in comparing with other methods such as value-at-risk (VaR) and mean-variance in which it is coherent and convex in stochastic programming [17]. CVaR is formulated as follows.

\[
\min \xi, \eta_\pi \quad \xi + \frac{1}{1 - \beta} \sum_w \eta(w). \pi(w)
\]  

subject to:

\[
\text{Cost}(w) - \xi - \eta(w) \leq 0; \forall w
\]  

(8)

\[
\eta(w) \geq 0; \forall w
\]  

(9)

Where the optimal value of \( \xi \) represents VaR and \( \eta(w) \) is a scenario-dependent variable that is equal to the difference between the cost of scenario \( w \) and VaR [4]. Note that \( \beta \) is the confidence level and in most problems it is assumed to be 0.95.

• Overall cost function

Based on the above terms, the overall cost function is mathematically modeled as follows. Note that, all terms are presented in $ values. Note also that the total number of scenarios is equal to the number of DR scenarios multiplied by the number of pool scenarios.

\[
\min_{\pi^D(t), \pi^P(t), P^F(t), \xi, \eta_\pi, d(t)} \quad CF = \sum_w \pi(w') \sum_{t \in T} \left[ \sum_{j \in J} P^F(w', t) \tilde{P}^D_j(t) R^D_j(t) \cdot d(t) \right]
\]  

\[
+ \sum_{t \in T} P^P(t, w') \lambda^P(t, w') \cdot d(t)
\]  

\[
+ \rho \cdot \left( \xi + \frac{1}{1 - \beta} \sum_w \eta(w). \pi(w) \right)
\]  

(10)

where \( \rho \) is the risk factor showing the risk averseness of the retailer.

The cost function is subject to the following enforcements:

- Equations (1)-(4) as DR cost constraints;
- Expressions (8), (9) as CVaR constraints;
- Energy balance equation as below:

\[
P^{\text{REQ}}(t) = P^P(t, w') + P^D(t)
\]  

(11)

V. CASE STUDY

A. Data

As stated earlier, an hour-ahead market is assumed in this paper. Based on this market scheme, the validity of the proposed method is evaluated using the duration of two peak hours. In this way, the Queensland market price data spanning January 2011 are used to generate pool price scenarios. Note that, pool scenarios are simply generated using the Autoregressive Integrated Moving Average (ARIMA) model. Furthermore, for each price value, four scenarios, representing DR participation factor, are randomly generated.

A portion of total peak load in the Queensland jurisdiction has been considered as the hourly load of the retailer (Table I).

<table>
<thead>
<tr>
<th>Total Load (MW)</th>
<th>Hour1</th>
<th>Hour2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2000</td>
<td>3000</td>
</tr>
</tbody>
</table>

In addition, Fig. 2 illustrates the reward-based curve considered in this paper. This curve is assumed to be identical for both two hours.

![Figure 2. Considered reward-based curve](image)

B. Experimental Results

The proposed problem is formulated in mixed-integer linear programming and solved using CPLEX under General Algebraic Modeling System (GAMS) [18].

In order to evaluate the impact of the uncertainty of both pool prices and DR, four cases are compared: C1) both pool prices and customers’ participation in DR are intermittent; C2) only the pool market involves uncertainty. DR is assumed to be deterministic (the given participation factor is equal to 1); C3) only DR is faced by intermittency. The pool price at each hour is calculated by averaging the price scenarios of that hour; C4) both the pool and DR are deterministic resources.

Tables II and III represent the procured energy from the pool and DR for different risk factors (\( \rho \)) in all given cases at hours 1 and 2, respectively. Note that case 4 is deterministic and hence, its outcomes are free from the risk factor. However, for the sake of comparison, we put its results identically for all risk factors.
TABLE II. ENERGY PROCURED FROM THE POOL AND DR AT HOUR 1

<table>
<thead>
<tr>
<th>DR Energy (MWh)</th>
<th>Pool Energy (MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1   C2   C3   C4</td>
<td>C1   C2   C3   C4</td>
</tr>
<tr>
<td>ρ</td>
<td>C1   C2   C3   C4</td>
</tr>
<tr>
<td>0 102 180 106 180</td>
<td>1898 1820 1894 1820</td>
</tr>
<tr>
<td>0.5 170 300 0 180</td>
<td>1830 1700 2000 1820</td>
</tr>
<tr>
<td>1 203 360 0 180</td>
<td>1796 1640 2000 1820</td>
</tr>
<tr>
<td>2 238 420 0 180</td>
<td>1762 1580 2000 1820</td>
</tr>
<tr>
<td>3 272 420 0 180</td>
<td>1728 1580 2000 1820</td>
</tr>
<tr>
<td>4 272 480 0 180</td>
<td>1728 1520 2000 1820</td>
</tr>
<tr>
<td>9 306 480 0 180</td>
<td>1694 1520 2000 1820</td>
</tr>
</tbody>
</table>

TABLE III. ENERGY PROCURED FROM THE POOL AND DR AT HOUR 2

<table>
<thead>
<tr>
<th>DR Energy (MWh)</th>
<th>Pool Energy (MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1   C2   C3   C4</td>
<td>C1   C2   C3   C4</td>
</tr>
<tr>
<td>ρ</td>
<td>C1   C2   C3   C4</td>
</tr>
<tr>
<td>0 93 180 97 180</td>
<td>2907 2820 2903 2820</td>
</tr>
<tr>
<td>0.5 124 240 0 180</td>
<td>2876 2760 3000 2820</td>
</tr>
<tr>
<td>1 156 300 0 180</td>
<td>2844 2700 3000 2820</td>
</tr>
<tr>
<td>2 187 360 0 180</td>
<td>2813 2640 3000 2820</td>
</tr>
<tr>
<td>3 218 420 0 180</td>
<td>2782 2580 3000 2820</td>
</tr>
<tr>
<td>4 218 420 0 180</td>
<td>2782 2580 3000 2820</td>
</tr>
<tr>
<td>9 279 480 0 180</td>
<td>2751 2520 3000 2820</td>
</tr>
</tbody>
</table>

From the above tables, the following points can be interpreted:

1. Energy purchased from DR is much higher in case 2 than case 1. For instance, the average share of DR in case 2 is about 70% higher than case 1 at hour 1. This value is around 90% at hour 2. This means once DR uncertainty is taken into account, retailers massively reduce their energy share from this resource. In this situation, they rely on the pool as the commonly used market.

2. In case 3, only a risk-neutral retailer (ρ = 0) buys a percentage of its energy from DR. Conservative retailers purchase only from the pool as its price is assumed to be deterministic in case 3. This is reasonable since as the retailer becomes more risk averse, it prefers to buy its energy from reliable resources (the pool in case 3).

3. The volume of DR in case 4 is equal to 180MW. Needless to say, this value is risk free, but it is put identically for all risk factors. It should be noted that DR share in case 4 is higher than case 3. The reason is that DR is a reliable resource in case 4, while it involves uncertainty in case 3.

Table IV provides the offered rewards to DR participants. It can be observed that the rewards offered in cases 1 and 2 are equal for most of risk factors. On the other hand, based on tables II and III, a retailer achieves more DR in case 2 than case 1. This means that a retailer achieves higher share of DR by neglecting the uncertainty of this resource though it offers the same reward as the case of including this intermittency. This is also true in cases 3 and 4. Both offers $98/MWh, while the DR share in case 4 is much higher than case 3. Note in case 3 that only a risk-neutral retailer pays incentive to customers ($98/MWh).

TABLE IV. OFFERED REWARD TO CUSTOMERS ($/MWh)

<table>
<thead>
<tr>
<th>DR Energy (MWh)</th>
<th>Pool Energy (MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1   C2   C3   C4</td>
<td>C1   C2   C3   C4</td>
</tr>
<tr>
<td>ρ</td>
<td>C1   C2   C3   C4</td>
</tr>
<tr>
<td>0 98 98 98 98</td>
<td>98 98 98 98</td>
</tr>
<tr>
<td>0.5 106 106 - 98</td>
<td>102 102 - 98</td>
</tr>
<tr>
<td>1 110 110 - 98</td>
<td>106 106 - 98</td>
</tr>
<tr>
<td>2 114 114 - 98</td>
<td>110 110 - 98</td>
</tr>
<tr>
<td>3 118 114 - 98</td>
<td>114 114 - 98</td>
</tr>
<tr>
<td>4 118 118 - 98</td>
<td>114 114 - 98</td>
</tr>
<tr>
<td>9 122 118 - 98</td>
<td>118 118 - 98</td>
</tr>
</tbody>
</table>

In order to compare the impact of the volatility of resources, in particular DR, on the cost value of all cases, we compute the cost and its standard deviation for each case. Note that, case 4 is not faced by the uncertainty and therefore, no deviation is expected in its cost, which is $512,611. Furthermore, in case 3, only a risk-neutral retailer buys from DR where its cost is $513,394 with the standard deviation of $9,762. The total cost is the same for other risk factors of this case ($514,420).

Fig. 3 depicts the expected costs of cases 1 and 2 as a function of their standard deviation for different risk factors. As can be seen, as the retailer takes more risk, the expected costs of both cases decrease while on the other hand, their standard deviation increases. However, the incremental rate of the standard deviation is higher than the falling rate of the expected cost. This means risky retailers are expected to buy their energy in lower costs while facing much higher cost fluctuations.

Figure 3. The expected cost versus standard deviation
Another interesting point in Fig. 3 is the difference between the trends of cases 1 and 2. In order to clarify this difference, Table V exhibits the changes of the expected cost and standard deviation in case 1 than case 2.

<table>
<thead>
<tr>
<th>( \rho )</th>
<th>Expected Cost Changes in C1 than C2</th>
<th>Standard Deviation Changes in C1 than C2</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.16%</td>
<td>1.77%</td>
</tr>
<tr>
<td>0.5</td>
<td>-0.05%</td>
<td>3.74%</td>
</tr>
<tr>
<td>1</td>
<td>-0.29%</td>
<td>5.18%</td>
</tr>
<tr>
<td>2</td>
<td>-0.61%</td>
<td>6.76%</td>
</tr>
<tr>
<td>3</td>
<td>-0.53%</td>
<td>6.80%</td>
</tr>
<tr>
<td>4</td>
<td>-1.01%</td>
<td>8.52%</td>
</tr>
<tr>
<td>9</td>
<td>-0.92%</td>
<td>8.67%</td>
</tr>
</tbody>
</table>

As can be seen, the differences between the expected costs of both cases are not very significant. In the worst situation, the expected cost of case 1 is 1% lower than case 2. On the other hand, it can be observed that the difference of standard deviations in these cases is relatively high. This dissimilarity is more notable once the risk factor increases. For instance, the standard deviation of case 1 is around 9% higher than case 2 for \( \rho = 9 \). This means ignoring the uncertainty of DR considerably changes the expected cost deviation. In other words, these results show how neglecting DR uncertainty may mislead a retailer in its expected outcomes. Note that, this misleading also happens in case 3 in compared to case 4 where high cost fluctuation ($9,762) is resulted once DR uncertainty is modeled in case 3.

VI. CONCLUSIONS

This paper evaluates the validity of employing real-time uncertain DR in short-term energy problems of retailers. It is assumed that a retailer intends to buy its required energy from pool markets and DR. For this purpose, a reward-based DR is mathematically formulated in which the unpredictable behavior of customers is modeled through a proposed scenario-based participation factor. Four distinct cases are defined to evaluate the impact of the uncertainty of both resources, especially DR, on short-term energy decisions of retailers. As a whole, the main findings of the paper are as follows:

1. DR programs are beneficial for short-term decisions of electricity retailers;
2. Ignoring the uncertainty of DR does not have a significant impact on the expected cost of retailer’s energy. However, it may mislead the retailer in its energy decisions in which 1) it may influence the retailer to rely more on DR while it may not be achievable in reality, and 2) the retailer may underestimate the expected cost deviation.

This paper clearly demonstrates the importance of incorporating the unpredictable behavior of customers in DR models, which is particularly critical for conservative retailers intending to employ real-time DR.

VII. REFERENCES

A New Trading Framework for Demand Response Aggregators

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Abstract- This paper proposes a new trading framework which allows demand response (DR) aggregators to procure DR from consumers and sell it to purchasers. The aggregator obtains DR from the proposed price and incentive-based DR programs. On the other side, the DR outcome is sold to purchasers through the proposed agreements, namely fixed DR contracts and DR options. The presented problem is formulated as a stochastic programming approach, where its feasibility is studied on a case of the Australian National Electricity Market (NEM).

Index Terms- Demand response, DR aggregator, DR options, fixed DR agreements, reward-based DR, time-of-use, stochastic programming

I. INTRODUCTION

A. Basic Concepts, Literature Review and Approach

Demand Response is a well-known strategy, which is employed by various electricity market players. For instance, market operators use DR to satisfy both market and power system security. DR is beneficial to transmission network providers to maintain their network secure and reliable. Retailers employ DR to hedge against the risk of spot market volatilities.

Various investigations have been addressed to facilitate the use of DR. One group of studies discusses the DR theory (see [1] and [2]) and formulate distinct DR programs such as incentive-based DR [3, 4] and price-based programs [5, 6]. The second group delivers the smart grid technologies such as Home Energy Management (HEM) systems [7, 8] and bi-directional communications between consumers and DR seekers [9]. In addition, some papers provide detailed control strategies for managing electrical loads such as water heater and air conditioners [10, 11].

DR aggregators can also play a vital role in enhancing DR. They indeed implement various DR programs on consumers to sell the outcome to other market players such as transmission network providers. A few papers address this topic in the literature. Authors in [12] propose a new DR market, which allows aggregators to sell their product through a pool-based market. The impact of aggregating DR on electricity markets is evaluated in [13]. A hierarchical market model is developed in [14], where aggregators are considered as a broker between residential end users and the market operator. With the aim of maximizing social welfare, paper [15] proposes a decomposition algorithm to ease implementing DR by aggregators.

This paper proposes a new trading framework for a DR aggregator. The aggregator acquires DR by implementing time-of-use (TOU) and reward-based DR programs on consumers. The behavior of consumers in the TOU program is modeled through elasticity factors, while in the reward-based DR it is demonstrated using uncertainty characterization. The obtained DR is then sold to purchasers through two proposed contracts: A fixed DR contract is formulated, in which the aggregator can sell a certain amount of DR in a specific price for a given time period. In addition, a DR option agreement is proposed, which gives the aggregator a right to exercise the contracted DR only if it is profitable.

The problem is formulated in a stochastic profit function, which is solved using GAMS. A case of the Australian National Electricity Market (NEM) is used to assess the validity of the proposed trading framework.

B. DR in the Australian NEM

DR is still at an early stage in the Australian NEM. Many challenges such as customers’ unwillingness to participate in DR, lack of enough knowledge and training, lack of proper metering facilities (smart metering), as well as market barriers such as market policies are key drivers.

The peak demand growth rate has become worse in the NEM over the past few years. This growth rate between 2005 and 2011 was about four times higher than the rate of energy growth [16]. It is estimated that approximately 25% of retail electricity costs come from peak events even though they occur for a period of less than 40 hours a year [16].

Considering the above issues, DR is becoming more important in Australia. The Ministerial Council on Energy of Australia asked the Australian Energy Market Commission (AEMC) to facilitate an efficient demand side participation (DSP) in the NEM. Consequently, a comprehensive investigation has been taken by the AEMC [17]. As one of the solutions proposed to enhance the DR outcome, the AEMC emphasizes the importance of market parties’ roles in assisting
DR. Among all parties, aggregators are invited to become more active in implementing DR programs on consumers. This is also given more attention in practice in the NEM. For instance, EnerNOC [18] currently provides DR to TransGrid, the transmission network service provider in New South Wales (NSW), Australia.

According to the AEMC report, it is estimated that the load reduction in three major states of Australia (NSW, QLD, and VIC) would be from 400 MW to over 1300 MW by 2020 [17]. This would lead a cost saving of between $4.3 and $11.8 billion over the next ten years, which equates to 3-9% of total forecast expenditure on the supply side.

The rest of the paper is organized as follows. Section II addresses the proposed DR trading framework. The profit function is formulated in section III. Section IV discusses the case study and results. Last section concludes the paper.

II. TRADING FRAMEWORK

The proposed DR trading framework is given in Figure 1. Electricity consumers include industrial, commercial and residential sectors. Each sector is offered a unique time-of-use tariff and a distinctive reward-based DR. On the other side, the aggregator trades the DR product with purchasers through fixed DR contracts and DR option agreements. Note that double-sided arrows indicate that the energy flow can be either from consumers to DR purchasers or in the opposite direction. That is, while the aggregator achieves DR to sell to buyers during peak time, it encourages consumers to consume more energy during off-peak periods, where the required energy is provided by DR purchasers.

![Figure 1. The DR Trading Framework](image)

A. Time-of-Use program

Time-of-use (TOU) programs are well-known in the power industry. According to this program, consumers receive distinct price tariffs during a day, for example peak and off-peak tariffs. Consequently they manage their electricity usage depending on how elastic they are to price changes. If they are highly elastic, the response is high and vice versa.

The TOU program is formulated in (1), where it is obtained from all consumers \( c = 1, 2, \ldots, N \) over the given horizon \( T \).

\[
E(TOU) = \sum_{c=1}^{N} \sum_{t=1}^{T} D_0(c, t) \cdot \sum_{p} E(c, t, p) \cdot \left( \frac{\lambda(c, p) - \lambda_0(c, p)}{\lambda_0(c, p)} \right) \cdot d(t) \quad (1)
\]

\( \lambda_0(c, p) \) indicates the initial price dedicated to consumer \( c \) in period \( p \). \( \lambda(c, p) \) shows the TOU price offered to consumer \( c \) in period \( p \). \( E(c, t, p) \) is the elasticity of consumer \( c \) during time \( t \) with regards to the electricity price in period \( p \). \( D_0(c, t) \) represents the initial demand of consumer \( c \) within time \( t \). Finally, \( d(t) \) represents the duration of time \( t \).

B. Reward-based DR

The reward-based DR is described in a stepwise function as shown in Figure 2.

![Figure 2. Reward-based DR curve](image)

According to this figure, the amount of load reduction grows in a stepwise manner as the aggregator offers higher rewards. This function is expressed in the following equations:

\[
P^{DR}(t) = \sum_{w} \pi(w) \cdot \sum_{j=1}^{N_j} PF(w, t) \cdot \tilde{R}^{DR}_j(t) \cdot v_{DR,j}(t) \quad (2)
\]

\[
R^{DR}(t) = \sum_{j=1}^{N_j} \tilde{R}^{DR}_j(t) \quad (3)
\]

\[
\tilde{R}^{DR}_{j-1}(t) \cdot v_{DR,j}(t) \leq R^{DR}_j(t) \leq \tilde{R}^{DR}_j(t) \cdot v_{DR,j}(t) \quad (4)
\]

\[
\sum_{j=1}^{N_j} v_{DR,j}(t) = 1 \quad (5)
\]

\( P^{DR}(t) \) refers to the total reduced load through implementing DR, and \( R^{DR}(t) \) indicates the reward paid to DR participants. Furthermore, \( v_{DR,j}(t) \) is a binary variable showing the level of the reduced load in the DR curve. \( PF(w, t) \) is a scenario-based participation factor which models the uncertainty of customers’ behavior. This factor ranges
between 0 and 1, where zero means no reward-based DR is attainable and \( PF(w, t) = 1 \) indicates that the anticipated DR is accessible. Finally, \( \pi(w) \) is the probability of scenario \( w \).

The overall reward-based DR is given in (2):

\[
EC(RDR) = \sum_{w \in W} \pi(w) \cdot \sum_{t=1}^{T} \sum_{j=1}^{N_j} PF(w, t) \cdot \lambda^R_j(t, R^R_j(t), d(t))
\]

C. Fixed DR contract

A fixed contract is an agreement between buyers and sellers of an asset, which is traded in a future time [19]. Considering this concept, a fixed DR contract is proposed here in which the aggregator trades DR with purchasers.

Fixed DR contracts are offered in various blocks, where each one involves a fixed amount of DR and price:

\[
C(FDR) = \sum_{t=1}^{T} \sum_{f=1}^{N_{FDR}} \sum_{b=1}^{N_{BDR}} P_{dbl}^R(t) \cdot \lambda^R_{f, b}(t, d(t))
\]

\[
P_{dbl}^{R\text{MIN}}(t) \leq P_{dbl}^R(t) \leq P_{dbl}^{R\text{MAX}}(t)
\]

The marginal size of each contract’s block is imposed by (8). \( P_{f, b}^R(t) \) and \( \lambda^R_{f, b}(t) \) are the power and the price of the \( b \)th block of fixed DR \( f \). The number of contracts is given by \( N_{FDR} \) and the number of blocks is represented by \( N_{BDR} \).

D. DR Option Agreement

A DR option is proposed in which the aggregator is given the right but not an obligation to trade DR with purchasers. This means that the DR aggregator signs this agreement at the beginning of the decision time horizon. However, exercising the contract at the energy delivery time depends on whether it is profitable or not. If the aggregator refuses to exercise the contracted DR option, it has to pay a predetermined penalty fee to the DR purchaser.

The DR option agreement is mathematically formulated in (9).

\[
\begin{align*}
C(DRO) &= \sum_{t \in T} \sum_{op=1}^{N_{op}} \bigg[ P_{op}(t), \lambda_{op}(t), v_{op}(t), d(t) \\
&\quad - \big( 1 - v_{op}(t) \big) \cdot f_{op}^{pen}(t) \bigg] \\
P_{op}^{MIN}(t) \leq P_{op}(t) \leq P_{op}^{MAX}(t) \quad \forall op = 1, 2, \ldots, N_{op}
\end{align*}
\]

Equation (9) consists of two terms addressing the revenue of practicing the DR option and the penalty of not exercising the signed contract. \( P_{op}(t) \) and \( \lambda_{op}(t) \) are the power traded in the DR option \( op \) and its price during time \( t \). Binary variable \( v_{op}(t) \) indicates whether the contract is exercised or not. \( f_{op}^{pen}(t) \) is the penalty of not exercising the option during time \( t \). \( N_{op} \) presents the number of DR options. Equation (10) imposes the upper and lower limits for each DR option.

### III. Problem Formulation

The overall problem is formulated as a profit function represented by (11). It consists of the revenue of selling DR through fixed DR contracts and DR option agreements, as well as the cost of the reward-based DR. The last component is CVaR, which is weighted using the risk factor (\( \rho \)). \( \xi \) and \( \eta_w \) are auxiliary variables for calculating CVaR [20]. \( \beta \) is the confidence level, which usually equals to 0.95. Note that the risk level (\( \rho = [0-\infty] \)) represents the trade-off between the expected profit and the risk.

\[
\begin{align*}
\text{Max} & \sum_{t=1}^{T} \bigg( \sum_{f=1}^{N_{FDR}} \sum_{b=1}^{N_{BDR}} P_{f, b}^R(t) \cdot \lambda^R_{f, b}(t, d(t)) \\
&\quad + \sum_{op=1}^{N_{op}} \big[ P_{op}(t) \cdot \lambda_{op}(t) \cdot v_{op}(t), d(t) \\
&\quad - \big( 1 - v_{op}(t) \big) \cdot f_{op}^{pen}(t) \bigg] \bigg) \\
&\quad + \sum_{p=1}^{P} \sum_{c=1}^{C} D_{c}(c, t) \cdot \sum_{p=1}^{P} E(c, t, p) \cdot \frac{(\lambda(c, p) - \lambda_{0}(c, p))}{\lambda_{0}(c, p)}
\end{align*}
\]

It should be noted that it is assumed consumers have smart meters and therefore the cost of installing meters is not included in the profit function. The profit function is subject to the following constraints:

- CVaR constraints

\[
-\text{Profit}(w) + \xi - \eta(w) \leq 0; \quad \forall w
\]

- Power balance equation (14):

\[
\sum_{op=1}^{N_{op}} P_{op}(t), v_{op}(t)
\]

\[
\begin{align*}
&\quad + \sum_{f=1}^{N_{FDR}} \sum_{b=1}^{N_{BDR}} P_{f, b}^R(t), \lambda^R_{f, b}(t, d(t)) \\
&\quad = P^R(t) \\
&\quad - \sum_{c=1}^{C} D_{c}(c, t) \cdot \sum_{p=1}^{P} E(c, t, p) \cdot \frac{(\lambda(c, p) - \lambda_{0}(c, p))}{\lambda_{0}(c, p)}
\end{align*}
\]

IV. Case Study

A. Data

The highest consumption day of Queensland in 2013 occurred in summer (January 9th). The load curve of this day is shown in Figure 3.
A working day in summer is also considered in this study, which is divided into two periods, peak and off-peak. Peak time is between 9am and 10pm, while other times are considered as off-peak periods. It is assumed that the aggregator buys DR from consumers to sell it to purchasers during peak time, while this flow is reverse during off-peak periods. Industrial, commercial, and residential consumers are considered here. TOU prices for each consumer are derived from retail tariffs in Queensland, Australia [21]. The elasticity matrix is provided in Table I [5]. Unique reward-based DR curves involving 25 steps are assumed for each sector. Furthermore, for each reward-based DR, 20 scenarios representing consumer uncertainties are randomly generated.

A fixed DR contract involving six blocks is considered for each period. The maximum demand of each block is 90kW and 30kW during peak and off-peak periods, respectively. Finally, four DR option agreements are modeled for each period, where the penalty of not exercising each agreement is assumed to be 10% of the contract’s value.

### Table I. Elasticity Matrix

<table>
<thead>
<tr>
<th></th>
<th>Peak</th>
<th>Off Peak</th>
</tr>
</thead>
<tbody>
<tr>
<td>Residential</td>
<td>-0.15</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>0.02</td>
<td>-0.03</td>
</tr>
<tr>
<td>Commercial</td>
<td>-0.16</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>0.03</td>
<td>-0.04</td>
</tr>
<tr>
<td>Industrial</td>
<td>-0.2</td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td>0.07</td>
<td>-0.08</td>
</tr>
</tbody>
</table>

### B. Experimental Results

The problem is formulated in a mixed-integer linear programming approach and is solved for different risk levels using CPLEX under GAMS [22]. Figure 4 depicts the TOU outcome. It can be seen that consumers reduce their consumption during peak, while they use more energy during off-peak time. The reduction during peak time is approximately 7% and the load growth in off-peak periods is 5.54%. Note that since the outcome of the TOU only depends on consumers’ elasticity, it is constant for various risk levels.

![Figure 4. TOU results](image)

Figure 4 illustrates the reward-based DR achievements. Increasing the risk level leads a declining trend in this program. This is reasonable since this program involves uncertainty and hence conservative aggregators prefer to reduce their share from it. It should be noted that negative values during off-peak periods mean that the aggregator sell the reward-based DR to consumers. In other words, consumers are encouraged to consume more energy through this program during off-peak.

![Figure 5. Reward-Based DR results](image)

Table II shows the energy traded in fixed DR contracts. The aggregator sells DR to purchasers in the peak period, while it buys energy during off-peak time. It can also be said that the conservative aggregator ($\rho = 2$) trades more fixed DR than the risk-neutral one ($\rho = 0$) in both periods.

### Table II. Fixed DR Energy (kWh)

<table>
<thead>
<tr>
<th>$\rho$</th>
<th>Peak</th>
<th>Off Peak</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>4559</td>
<td>-1004</td>
</tr>
<tr>
<td>1</td>
<td>4539</td>
<td>-1004</td>
</tr>
<tr>
<td>2</td>
<td>4735</td>
<td>-1074</td>
</tr>
</tbody>
</table>

Table III represents the exercised DR options for different risk levels. All DR options are used for risk factors 0 and 1. For $\rho = 2$, DR options (DROP) 1 and 3 are not exercised during peak and off-peak periods, respectively. This trend
indeed follows the declining tendency of the reward-based DR as a result of increasing the risk level.

Finally, the impact of the unpredictable behavior of consumers is evaluated here. Two cases are considered: Case 1 represents the outcome when the uncertainty is modeled (for the risk-neutral aggregators) and case 2 ignores the unpredictable behavior of customers ($PF(w, t) = 1$ in the reward-based DR). The amounts of TOU and DR options remain constant in both cases. But the reward-based DR and fixed DR contracts change as Figure 6. As can be seen, disregarding the behavior leads to a higher reward-based DR outcome and consequently, higher amounts of fixed DR. This indeed shows how ignoring customers’ behavior may mislead the aggregator in its energy plan.

![Figure 6. Impact of uncertain behavior of consumers on DR outcomes](image)

**TABLE III. DR OPTION EXERCISMENT**

<table>
<thead>
<tr>
<th>$\rho$</th>
<th>Peak</th>
<th>Off Peak</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>All</td>
<td>All</td>
</tr>
<tr>
<td>1</td>
<td>All</td>
<td>All</td>
</tr>
<tr>
<td>2</td>
<td>DROP2-DROP4</td>
<td>DROP1, DROP2, DROP4</td>
</tr>
</tbody>
</table>

V. CONCLUSIONS

This paper proposes a new trading framework for DR aggregators, which allows them to play an arbitrator role between consumers and market participants. TOU and reward-based DR programs are modeled to be applied to consumers. On the other hand, the aggregator is able to trade the DR product with purchasers through the proposed fixed-DR and DR option agreements. The problem is formulated using a mixed-integer profit function, which is evaluated on a case of the Australian national electricity market. The main findings are as follows:

1. The proposed framework helps the aggregator to become more active in the DR market. In this framework the aggregator can provide a bidirectional energy flow between consumers and DR purchasers.

2. The uncertainty of customers’ behavior has an important impact on the decisions of the aggregator. Modeling the behavior results in distinct decisions for various risk levels. In addition, disregarding this uncertainty misleads the aggregator in its DR strategy.

VI. REFERENCES


Demand Response Application by Strategic Wind Power Producers

Nadali Mahmoudi, Student Member, IEEE, Tapan K. Saha, Senior Member, IEEE, and Mehdi Eghbal, Member, IEEE

Abstract—This paper considers a wind power producer playing strategically in a day-ahead market while willing to sell demand response (DR) contracts with a DR aggregator. To this end, a bilevel problem including a single leader and two followers is formulated. The wind power producer is the leader aiming at maximizing its profit through offering into a day-ahead market and clearing its deviation in a balancing market. The strategic behavior of the producer in the day-ahead market is modeled through the market clearing process (follower 1). In addition, the DR aggregator behavior is modeled through a revenue function in which the aggregator is able to sell its DR product to the wind power producer, other competitors and the day-ahead market (follower 2). The overall problem is a stochastic mathematical program with equilibrium constraints (MPEC) in which wind power production and imbalance prices are associated with uncertainty. The problem is then transformed into a linear programming approach. A case of the Nordic market is chosen to assess the validity of the given problem.

Index Terms—Bilevel programming, demand response, DR aggregator behavior, MPEC, social welfare, stochastic programming, strategic wind power producer

NOMENCLATURE

$C^{DR,T}(t)$: Total DR capacity

$P^D(du,db,t)$: Demand scheduled of unit $du$, block $db$

$P^{DR}(t)$: DR obtained by the wind power producer

$P^{DR,DA}(dru,t)$: DR scheduled for aggregator unit $dru$

$P^G(gu,b,t)$: Power scheduled for generator unit $gu$, block $b$

$P^{imb}(t,w)$: Imbalance power by the wind producer

$P^{WDA}(wu,t)$: Wind power scheduled in the DA market for wind unit $wu$

$P^{WP}(t,w)$: Wind power production in scenario $w$

$P^{W,of}(wu,t)$: Offered wind power in the DA market

$p^{DMax}(du,db,t)$: Upper level of demand unit $du$, block $db$

$p^{DRMax}(dru,t)$: Upper level of DR unit $dru$

$p^{GMax}(gu,b,t)$: Upper level of generation unit $gu$, block $gb$

$sp^C(c,t,s)$: DR share percentage of competitor $c$ in scenario $s$

$sp^{DR,DA}(dru,t)$: DR share percentage of the DA market

$sp^W(t,s)$: DR share percentage of the wind producer

$\lambda^{DA}(t)$: DA market price

$\lambda^D(du,db,t)$: Marginal utility of demand $du$, block $db$

$\lambda^C(c,t,s)$: DR price by competitor $c$ in scenario $s$

$\lambda^{DR}(t)$: DR price offered by the wind producer

$\lambda^{DR,DA}(dru,t)$: Marginal cost of DR unit $dru$

$\lambda^G(gu,b,t)$: Marginal cost of generator $gu$, block $b$

$\lambda^{imb}(t,w)$: Imbalance price in scenario $w$

$\lambda^{W,of}(wu,t)$: Offer price by the wind producer unit $wu$

$\xi$, $\eta(w)$: Auxiliary variable for CVaR calculation

I. INTRODUCTION

A. Background, aim, and approach

With various predetermined renewable energy targets, it is expected that wind power will rapidly grow in the near future. Some goals are for example 50% from wind in Denmark by 2020, 20% renewable energy (mostly wind production) in Australia and the European Union by 2020, and a 33% target in California by 2020 [1].

As wind power becomes matured enough in electricity markets, it is expected wind power producers are treated as similar to conventional power plants. To this end, they have to participate in the electricity market and place their energy and price offer. In addition, they are required to take the responsibility of their power imbalances between their offer and real production in the real time dispatch. This is currently applied for some wind power producers in real markets such as Western Denmark [2], Germany and Australia [1].

In addition, significant wind power penetration leads to new challenges. One important issue is that a wind power producer with high power production may become dominant in the market and plays strategically to change the market price. Indeed, exercising market power by power plants including wind power producers may happen in any electricity market. This is due to different circumstances, where one reason for exercising market power by wind power producers is their high power penetration. For instance, as reported in

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[3], the Danish Elspot areas, DK1 and DK2, had negative prices for 39 and 30 hours respectively in 2013, due to high wind power production. In addition, a study on the Nordic market [4] shows that producers with fluctuating production such as wind producers may act strategically in their bidding on the spot market due to the asymmetric cost of the regulating market. Note that the assumption of owning high wind power production by a wind power producer is not unrealistic as there are some real cases which the coordination of several wind farms is recommended as a solution to alleviate their production deviation [5, 6].

Furthermore, since the wind power producer is required to place its offer in the day-ahead market, which is several hours prior to the real time dispatch, it may face power production deviation in real time. This deviation is indeed required to be compensated in the balancing (regulating) market. However, there may be a possibility of price violations in this market. Hence, the producer can use flexible resources such as hydro, storage systems and thermal power plants to overcome the risk of facing the imbalance price violation [7-11]. Demand response (DR) is another resource which has recently been used for this purpose. DR is a fast and flexible resource which is growing rapidly around the world. For instance, according to a report by the Federal Utility Regulatory Commission, DR is capable to offset 20% of the peak demand in the US [12]. DR can be used in different markets, where for a system integrating wind power it is a useful tool to cope with the uncertainty of wind power production, both from the producer and ISOs’ perspectives.

This paper is motivated by the above issues, i.e. study of a strategic wind power producer which is responsible for its participation in the market and also can use DR to lessen the risk of uncertainty. An offering strategy for this producer is proposed as follows. The producer offers into the day-ahead market. It is assumed that the wind power producer is the only player with market power in this market while other participants are fully competitive. Consequently, a day-ahead market clearing process is modelled through which the wind producer can determine its power level and price in this market. In addition, the wind power producer uses DR to alleviate its power production deviation in the real-time dispatch. This paper proposes a DR scheme in which the wind power producer can bilaterally set a DR contract with a DR aggregator. The DR aggregator itself seeks to maximize its revenue from selling the DR product through three purchasers, namely, the wind power producer in this paper, the day-ahead market, and other players willing in DR. Note that trading DR through bilateral contracts exists in the real case [13]. In addition, DR aggregators can directly participate in some markets such as PJM [14].

The problem is formulated in a bilevel programming approach involving a single upper-level (leader) and two lower-level (followers) problems. The wind power producer’s objective is to maximize its profit, which is modelled in the upper-level problem. Social welfare maximization is formulated to represent the day-ahead market clearing process in lower-level problem 1. In addition, the aggregator behavior in selling DR to DR buyers is formulated through revenue maximization in lower-level problem 2. The given problem is a mathematical program with equilibrium constraints (MPEC), which is transformed into a single-level problem by replacing the lower-level problems with their Karush-Kuhn-Tucker (KKT) optimality conditions [15, 16]. The problem is then linearized using the strong duality theorem [15, 16] and the technique provided in [17]. The rendered problem is stochastic mixed-integer programming in which wind power production and imbalance prices are uncertain parameters. In order to model the risk, the CVaR measure is applied here. The problem is evaluated on a case of the Nordic market [18].

Note that the proposed approach is applicable in electricity markets integrating substantial wind power production. Such markets with the mentioned regulatory framework exist in the real world, where Western Denmark, Germany and the state of South Australia are the leaders. Note also that the market regulators are constantly updating the regulatory framework to overcome new issues. With regards to wind and renewable resources, for instance, they first initiated new policies and incentives such as feed-in-tariff (FIT) schemes to grow these resources. However, as these resources became significant in some countries such as Denmark and Germany, they changed the rules and policies. For instance, Denmark has replaced FIT with a fixed premium payment in 2000, which is paid on top of earing by wind farms in the market [1]. Furthermore, they may need to revise the rules and policies due to the significant increase of wind production which may bring several issues such as exercising market power. Therefore, the study of a price-maker wind producer may help the market regulator to better design rules and policies, which would result in increasing the competitiveness of the market [15].

B. Literature review and contributions

Offering strategies by fully competitive wind power producers are addressed in some studies. For instance, the concept of minimizing imbalance costs in wind offering strategies is investigated in [19]. Offering in various market floors including day-ahead, adjustment and balancing markets are addressed in [20]. Authors in [5] recommend the coalition of wind producers to alleviate wind power uncertainty.

Few papers have recently raised the issue of the market power capability by wind power producers. Ref. [15] is the most recent and comprehensive one. The authors investigate the high penetration of a wind producer by modelling it as a strategic player in both day-ahead and balancing markets. An equilibrium problem with equilibrium constraints (EPEC) is formulated to this end. Authors in [2] consider a wind power producer which is a price maker in the day-ahead market and a deviator in the balancing market. Unlike [2], wind power producer in [21] is fully competitive in the day-ahead market while having market power in the balancing market. Authors in [6] investigate the effect of a price-maker wind power producer on the market price. A study of the Nordic market in [3] indicates that producers with fluctuating production may act strategically in their bidding on the spot market due to the asymmetric cost of the regulating market.

As discussed earlier, wind power producers may use flexible resources to cope with their power production
uncertainty. This is addressed in some studies such as [7-11]. While hydro power plants are used in coordination with wind in [7, 9], references [8, 10] study the feasibility of using storage systems by wind power producers. In addition, authors in [11] recommend the coordinated trading of wind power producers and thermal energy. DR is also used for this purpose. However, it is mainly employed by market operators to improve market and network issues [22-24]. Few papers investigate the problem from a wind power producer’s point of view. For instance, authors in [25] propose a method in which a virtual power plant is modeled to coordinate wind power and demand response. Our very recent studies investigate the benefits of employing DR by wind power producers [26, 27].

This paper is in a common purpose with [2, 6, 15, 21], where it investigates the strategic offering of a wind producer. However, the main contributions of the paper are:

1- The paper proposes a new scheme in which a strategic wind power producer can use demand response in its energy offering in order to alleviate its production uncertainty risk. A bilateral DR contract is presented between the producer and a DR aggregator in which the DR aggregator behavior is taken into account.

2- The above problem is formulated in bilevel programming including a single leader and two followers. The linear form of this problem is then derived to be solvable using commercially available software.

3- The risk faced with the wind power producer is modeled using CVaR. The offering strategies of both risk-neutral and risk-averse wind power producers are investigated.

In addition, the impact of imbalance prices on the strategic behavior of each producer is studied.

The rest of the paper is structured as follows. Section II discusses the proposed offering strategy of a strategic wind power producer. The mathematical formulations of the proposed bilevel problem are addressed in section III. Section IV presents the equivalent linear formulation of the given bilevel problem. Section V provides a case study with numerical results. Conclusions are drawn in Section VI. Finally, appendices are addressed in the last section.

II. STRATEGIC WIND OFFERING

A. Framework

The following assumptions are considered. For the sake of simplicity, we assume the strategic behavior of a wind power producer in the day-ahead market only, which is similar to [2]. This is reasonable as the majority of the energy is traded in this market. In addition, the transmission network is not modeled in this paper, which makes the findings intuitive. This is a common assumption in wind offering studies such as [7, 10, 20]. Nevertheless, the network constraints can be modeled in the paper in a similar way to [2]. In addition, the balancing market is assumed to be settled in a single-price system, which is used in the US, instead of a dual-price scheme. Furthermore, similar to the existing studies, a single one hour period is chosen. However, the problem is also valid for multi-period problems. The problem size increases as the multi-hour model is considered. One simplification is provided in [2], where the problem is solved hour by hour for the entire day. This is justified since the wind power producer is not faced with ramp constraints due to its uncontrollable production. The problem without simplifications is complex and there are some solutions for it. If we consider the lower-level problem as a DC OPF, which is mainly used in the literature, the overall multi-period problem can be solved using a Benders’ Decomposition technique. To this end, the problem is decomposed into sub-problems, one per each time and each scenario, which can be solved separately with the reduced computational burden [28]. For the complicated systems such as multi-area one, there is a need for approaches such as the augmentation Lagrangian relaxation [29] or the model which solves non-convexities of the market pricing in [30]. This is not the focus of our work as we seek to show the feasibility of employing DR by strategic wind power producers.

The proposed bilevel problem is depicted in Fig. 1. Note that parameters in each level are shown by dash line boxes and arrows, while the decision variables are represented using solid line boxes and arrows. In addition, the links between different levels of the problem are indicated by double lines.

The procedure carried out in this bilevel problem is as follows. In the upper-level problem, the wind power producer (WPP) makes two decisions: D1 the day-ahead offer; D2 the DR price given to the DR aggregator. The day-ahead (DA) offer includes the energy volume and price for each dispatch interval. This decision is faced with the uncertainty involved in the power production and imbalance price forecasts. To this end, plausible realizations of these stochastic parameters are required to be taken into account. In addition, the level of the risk taken by the producer affects the DA offer decision. That is, the sale share of day-ahead and balancing markets may change in various risk levels. The day-ahead energy volume and price as well as the DR share procured by the wind power producer are the other factors that affect the DA offer. The former, i.e. the day-ahead energy volume and price, is decided in lower-level problem 1 through a market clearing process. To this end, offers from the wind power producer as well as other generators and the DR aggregator are stacked. On the other hand, demand bids are also received. Consequently, the day-ahead market price and energy volume are determined from the intersection of supply and demand curves (See lower-level problem 1). The latter, i.e. the DR share procured by the wind power producer, is decided in lower-level problem 2. In a revenue maximization problem, the DR aggregator determines the DR share to be sold to three DR purchasing: the wind power producer, other DR buyers and the day-ahead market. This decision is made according to the prices offered by the DR purchasers. Note that the DR price offered by the wind power producer is decided in the upper level problem as decision 2 (D2). The wind power producer decides on this price based on the day-ahead price (derived in lower-level problem 1) and an anticipation of DR prices offered by other DR purchasers (See the upper-level problem, right-hand side).

B. Uncertainty characterization

Each upper-level scenario is represented by scenario w,
which comprises a vector of imbalance prices \( \lambda^{imb}(t,w) \) and wind power production \( P^{WP}(t,w) \).

\[
\text{scenario } w = \left\{ \lambda^{imb}(t,w), P^{WP}(t,w) \right\}
\]

The probability of each scenario occurrence equals \( \pi(w) \), where \( \sum_{w \in W} \pi(w) = 1 \).

Each scenario in lower-level problem 2 is illustrated by scenario \( s \), which involves a vector of other competitors’ DR prices \( \lambda^c(t,s) \).

\[
\text{scenario } s = \left\{ \lambda^c(t,s) \right\}
\]

Similar to the upper-level problem, the probability of each scenario is \( \pi(s) \), where \( \sum_{s \in S} \pi(s) = 1 \).

Note that lower-level problem 1 is a deterministic problem and independent of scenarios.

### III. PROBLEM FORMULATION

The bilevel problem is formulated as follows.

\[
\begin{align*}
\text{Maximize} & \quad \sum_{w \in W} p^{WDA}(wu,t) + p^{imb}(t,w) = P^{WP}(t,w) + P^{DR}(t) \quad \forall t, \forall w \\
\text{Subject to} & \quad p^{WDA}(wu,t) + p^{imb}(t,w) = P^{DA}(t) \quad \forall \alpha \in \mathbb{A} \quad \forall w \\
& \quad P^{DA}(t) = c^{DR,T}(t) \sum_{s \in S} \pi(s) sp^W(t,s) \quad \forall t \\
& \quad \text{where } p^{WDA}(wu,t), \lambda^{DA}(t) \forall t \in \mathbb{A} \\
& \quad \text{Minimize } \sum_{w \in W} p^{WDA}(wu,t) + \sum_{w \in W} \sum_{g \in GU} \sum_{b \in B} p^{G}(gu,b,t) \\
& \quad + \sum_{dru \in DRU} \sum_{db \in DB} p^{DR,DA}(dru,t) \lambda^{DR,DA}(dru,t) \\
& \quad - \sum_{dru \in DRU} \sum_{db \in DB} p^{D}(du,db,t) \lambda^{D}(du,db,t) \\
& \quad \text{Subject to } \\
& \quad 0 \leq p^{WDA}(wu,t) \leq p^{W,of}(wu,t) \\
& \quad \lambda^{DA}(t) \leq \tau^{Min}(wu,t) \leq \tau^{Max}(wu,t) \quad \forall wu \\
& \quad 0 \leq p^{G}(gu,b,t) \leq p^{GMax}(gu,b,t) \\
& \quad \lambda^{DA}(t) \leq \alpha^{Min}(gu,b,t) \leq \alpha^{Max}(gu,b,t) \quad \forall wu, \forall gu, \forall b \\
& \quad 0 \leq p^{DR,DA}(dru,t) \leq p^{DRMax}(dru,t) \\
& \quad \theta^{Min}(dru,t) \leq \theta^{Max}(dru,t) \quad \forall dru
\end{align*}
\]

Fig. 1. Strategic wind offering considering the DR aggregator behavior
0 ≤ P^D(du, db, t) ≤ P^{DMax}(du, db, t)

\[ φ^{Min}(du, db, t), φ^{Max}(du, db, t), \forall du, \forall db \]
\{  \}

and \( sp^W(t, s) \forall t \in \arg \text{ Minimize} \)
\[ \text{MinusDR}_R = - \sum_{s \in S} π(s) \times C^{DR,t}(t) \times \left[ \left[ sp^W(t, s) \times λ^{DR}(t) + \sum_{c \in C} sp^C(c, t, s) \times λ^C(c, t, s) \right] - \sum_{dru \in DRU} sp^{DR,DA}(dru, t) \times λ^{DA}(t) \right] \]  \( \text{Subject to} \)  
\[ sp^W(t, s) + \sum_{dru \in DRU} sp^{DR,DA}(dru, t) + \sum_{c \in C} sp^C(c, t, s) = 1 \quad \forall s \]  
\[ : μ^W(t, s), μ^{DA}(dru, t), μ^C(c, t, s), \forall s, \forall c, \forall dru \]  

The upper-level problem is provided in (3)-(9). The profit function of the wind power producer is indicated in (3). The first term of this function shows the revenue obtained from selling into the day-ahead market. \( p^{WD,A}(wu, t) \) and \( λ^A(t) \) are decided in the day-ahead market clearing process, i.e., lower-level problem 1 (Eqs. (10)-(15)). The second term indicates the cost of DR. The third term is the revenue achieved from the balancing market. Note that if the wind power producer has deficit generation, it has to buy its deviation from the balancing market and hence, this term is a cost for the producer. Finally, the last term illustrates CVaR which is weighted using the risk factor (\( \rho \)). A risk level (\( \rho \)) closed to 0 means that the wind power producer is risk-neutral while larger risk levels model risk-averse producers. \( β \) is the confidence level, which is 0.95. Equation (4) enforces the power balance for the wind power production. Non-negativity of the wind power offer (\( p^{W,o}(wu, t) \)) in the day-ahead market is represented in (5). Expressions (6) and (7) represent CVaR constraints [20], which are derived to linearize this risk measure. Note that Profit(w) in (6) indicates the obtained profit for scenario w, as illustrated in (8). In (9), \( P^{DR}(t) \) is formulated as a function of the DR percentage (\( sp^W(t, s) \)) which the DR aggregator sells to the wind power producer. This DR share (\( sp^W(t, s) \)) is indeed a variable which is determined by the DR aggregator, i.e., lower-level problem 2 (Eqs. (16)-(18)).

Lower-level problem 1 is addressed in (10)-(15). This problem clears the day-ahead market. In order to make the canonical representation, the minus social welfare (MinusSW) is used in (10). The first three terms of this function respectively provide the offers by the wind power producer, other generators and the DR aggregator. The last term is the demand offer. The energy balance of the day-ahead market is imposed in (11). Constraints (12)-(15) respectively enforce the upper and lower limits of power for the wind power producer, other generators, the DR aggregator and the demand. Dual variables for each constraint are indicated following a colon.

As mentioned earlier, the DR percentage procured by the wind power producer (\( sp^W(t, s) \)) is determined in lower-level problem 2. This problem is addressed in (16)-(18). The DR aggregator’s objective function is shown in (16). Again, the minus revenue (MinusDR_R) is used in the objective function to make it canonical. The first two terms respectively indicate the expected revenues from the wind power producer as well as other players which are interested in buying DR. The last term represents the revenue obtained from selling DR to the day-ahead market. Note that this term is the product of two variables, i.e. \( sp^{DR,DA}(dru, t) \) and \( λ^{DA}(t) \). However, since these variables are decided in lower-level problem 1, this product is constant here and we can remove it from the objective function. Instead, a new constraint is added to the problem to relate lower-level problems 1 and 2:

\[ P^{DR,DA}(dru, t) = C^{DR,t}(t), sp^{DR,DA}(dru, t) \]  \( \text{Constraint (17) imposes that total DR share percentage must be equal to 1. Finally, constraint (18) is used for variable declarations. Again, dual variables for each constraint are indicated following a colon.} \)

It should be emphasized that the variables of lower-level problem 1 are \( p^{WD,A}(wu, t) \), \( P^{DC}(wu, t) \), \( p^{DR,DA}(dru, t) \), \( P^D(du, db, t) \), plus all dual variables shown in (11)-(15).

In addition, the variables of lower-level problem 2 include:

\[ Δ^{LL2} = \left\{ sp^W(t, s), sp^C(c, t, s), γ(t, s), μ^W(t, s), μ^C(c, t, s) \right\} \]

Finally, the upper-level variables contain all variables of lower-level problems 1 and 2 plus the following:

\[ Δ^{UL} = \left\{ λ^{DR}(t), p^{Inh}(t, w), λ^{W,o}(wu, t), P^{W,o}(wu, t) \right\} \]

IV. LINEAR FORMULATION

The given bilevel programming includes nonlinearity. This section provides an equivalent single-level linear problem which is easily solvable by commercially available software. To this end, the following procedure is applied.

First, the bilevel problem is transformed into a single-level MPEC. For this purpose, each lower-level problem is replaced by its first-order optimality conditions through the KKT conditions [16] (Appendix A). Note that this transformation is valid since the lower-level problems are continuous and linear and thus convex. The next step is to linearize the derived MPEC. Indeed, the MPEC is nonlinear as a result of 1) the complimentary conditions resulting from applying KKTs, and 2) the products of \( P^{WD,A}(wu, t) \times λ^{DA}(t) \) as well as \( P^{DR}(t) \times λ^{DR}(t) \) in (3). While the former is linearized using the method presented in [17] (Appendix A), the latter is linearized using the strong duality theorem [16] (Appendix B).

Overall, the equivalent single-level linear problem is as:
Maximize
\[
\sum_{wu \in WU} p^{WDA}(wu,t) \times \lambda^{DA}(t) - p^{DR}(t) \times \lambda^{DR}(t) + \sum_{w \in \Omega} \pi(w) \times p^{imb}(t,w) \times \lambda^{imb}(t,w) + \rho \times \left( \varepsilon - \frac{1}{1 - \beta} \sum_{w \in \Omega} \eta(w) \pi(w) \right), \forall t
\]
subject to
Constraints (4)-(9), (11)-(15), and (17)-(19);
Constraints (A1)-(A26).

The derived problem in (20) is a mixed-integer linear programming approach. Note that the linear equivalent of the product of \( P^{DR}(t) \) and \( \lambda^{DR}(t) \) as well as that of \( p^{WDA}(dru,t) \) and \( \lambda^{DA}(t) \) are respectively presented in (A29) and (A31) in Appendix B. Constraints (4)-(9), (11)-(15) and (17)-(19) of the original problem are applied here. (A1)-(A26) are associated with the KKT optimality conditions and the linearized complementarity slackness conditions (See Appendix A).

V. CASE STUDY

A. Data Preparation and Assumptions

The proposed offering strategy is assessed on a realistic case of the Nordic market [18]. Demand, generators and DR offers are depicted in Table I. The offers for demand and generators are taken from the Nordic market for hour 12 am on the 23th of January 2012. Since the cost offers of individual generators as well as demand are not publicly available, this paper uses the supply and demand curves of the aggregated generation and demand offers, which are represented in the market clearing price (MCP) model of the Nordic market for the relevant hour. However, DR offers are assumed since there is no DR data available. These offers are indeed chosen in such a way to be close to other generators’ offers. The assumption is reasonable since the DR aggregator needs to compete with other power plants to be able to sell its DR product in the market.

The upper-level scenarios are generated as follows. The wind power producer Hemmet located in Denmark is chosen [31]. The installed capacity is 27MW (Vestas Turbines). Wind speed scenarios are generated using the ARMA model where the available data in 2012 is used as input time series. 10 wind speed scenarios are generated. These scenarios are then transformed into power scenarios using the Vestas Wind Curve. Note that in order to make the wind power producer influential in the market, we consider a wind farm sized 200 times of the given farm, i.e. 5400MW capacity.

In addition, 10 imbalance price scenarios are generated. For this purpose, the ARIMA method is used. A time series of the prices of the Nordic market in 2012 is used to generate price scenarios.

In the lower-level problem, the rival DR prices, i.e. the DR price given to the DR aggregator by other players interested in DR, are considered to be stochastic. To this end, 3 players are taken into account. In addition, 3 scenarios are generated to represent the uncertainty of each rival competitor.

<table>
<thead>
<tr>
<th>OFFERS BY DEMAND, GENERATORS AND DR IN THE DAY-AHEAD MARKET</th>
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<tbody>
<tr>
<td><strong>Table I</strong></td>
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<tr>
<td><strong>Volume (MWh)</strong></td>
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<td>33662.2</td>
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<td>329.3</td>
</tr>
</tbody>
</table>

B. Numerical results

The proposed problem is solved for two risk levels using CPLEX 11.1.1 under GAMS [32]. The problem is solved on a personal computer with the processor of Intel® core™ i7 at 3.4GHz and RAM of 8GB. The model statistics are as follows. The number of single equations is 282 while the number of non-zero elements is 779. In addition, the numbers of single and discrete variables are respectively 256 and 79. The computation time for the optimal solution is 18.8s.

Day-ahead market clearing prices for two risk-levels are shown in Table II. Note that these prices are cleared as a result of exercising market power (strategic behavior) by the wind power producer. While the risk-neutral producer fixes the price at $30/MWh, the risk-averse producer tends to increase the price to $31/MWh. This is sensible since the risk-neutral producer prefers to have a higher sale share in the day-ahead market and therefore, keeps the price as low as possible to be successful in this market. On the other hand, the risk-averse producer is interested in selling more energy in the balancing market, where it has a better forecast of its production. Consequently, it increases the day-ahead price to compensate possible fluctuation (losses) in the balancing market.

<table>
<thead>
<tr>
<th>DAY-AHEAD MARKET CLEARING PRICE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Table II</strong></td>
</tr>
<tr>
<td><strong>Rho=0</strong></td>
</tr>
<tr>
<td><strong>DA Price ($/MWh)</strong></td>
</tr>
<tr>
<td>30</td>
</tr>
<tr>
<td><strong>Rho=10</strong></td>
</tr>
<tr>
<td><strong>DA Price ($/MWh)</strong></td>
</tr>
<tr>
<td>31</td>
</tr>
</tbody>
</table>

Table III provides the energy sold to the day-ahead market by the wind power producer (WPP), generation companies (GENCOs) and the DR aggregator. An interesting result is that as the risk level increases, the wind producer significantly decreases its participation in the day-ahead market. This indeed proves the discussion mentioned above. As a result of this declining trend and also because of the increased day-ahead price in risk level 10 (See Table II), the shares of other generators as well as the DR aggregator grow. Note that the total demand served in both risk levels is identical. Indeed, the last demand offer, i.e. (329.3MWh, $30/MWh) is not
approved in the day-ahead market in both risk levels.

<table>
<thead>
<tr>
<th>TABLE III</th>
<th>ENERGY VOLUME SOLD TO THE DA MARKET BY THE WPP, GENCOs AND THE DR AGGREGATOR (MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>WPP</td>
</tr>
<tr>
<td>Rho=0</td>
<td>4643</td>
</tr>
<tr>
<td>Rho=10</td>
<td>3493</td>
</tr>
</tbody>
</table>

Fig. 2 displays the energy volume traded by the wind power producer in the balancing market. The wind power producer in risk level zero has to buy around 370MWh from the balancing market to compensate its overbid in the day-ahead market. Actually, the expected production of wind power producer is around 4280MWh while its power sold in the day-ahead market is 4643MWh. On the other hand, the significant sale share of the risk-averse wind power producer (Rho=10) in the balancing market is obvious here.

![Fig. 2. Wind power participation in the balancing market](image)

The DR volume that the aggregator sells to each DR purchaser is depicted in Fig. 3. The risk-neutral wind power producer has no DR procurement from the DR aggregator while the risk-averse producer purchases 500MWh. This is reasonable since the risk-averse producer tends to buy DR to compensate its possible deviation in the real time. This tendency is confirmed in Table IV, where the risk-neutral wind power producer offers a DR price equal to $27.44/MWh while the risk-averse producer’s price given to the DR aggregator is $31/MWh. It is also obvious from Fig. 3 that the DR aggregator sells more DR to the day-ahead market in risk level equal to 10. This is as a consequence of the higher day-ahead price in this risk level compared to the risk level equal to zero (See Table II). Finally, as a result of the increment in the DR share of the wind power producer and the day-ahead market, that of other competitors declines in risk level 10.

![Fig. 3. DR Sold to different DR purchasers](image)

<table>
<thead>
<tr>
<th>TABLE IV</th>
<th>DR PRICE OFFERED BY THE WIND POWER PRODUCER</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Offered Price</td>
</tr>
<tr>
<td>Rho=0</td>
<td>27.44</td>
</tr>
<tr>
<td>Rho=10</td>
<td>31</td>
</tr>
</tbody>
</table>

C. Imbalance price sensitivity analysis

This section analyzes the impact of the imbalance price on the behavior models of the strategic wind power producer. Three cases are considered. Case1: the imbalance price is 95% of the original price used in the main study; Case2: the outcomes of the main study; Case3: the original imbalance price is increased 5%.

The day-ahead market clearing price is delivered in Table V. In addition, the wind power scheduled for different imbalance prices is provided in Fig. 4. It can be seen that the day-ahead price for case 1 in risk level 10 decreases compared to the main case, i.e. Case 2. The strategic wind power producer indeed bids in such a way to reduce the market price and consequently sells a higher portion of its production in the day-ahead market (See Fig. 4). This behavior is resulted since the imbalance price is low in Case 1 and therefore the producer can easily compensate its deviation from the day-ahead schedule in the balancing market at a low price. On the other hand, in case 3 where the expected imbalance price is high, both risk-neutral and risk-averse producers tend to increase the day-ahead market price. Therefore, the risk-neutral can increase its profit in a higher day-ahead price. In addition, this producer reduces its share in the day-ahead market with the hope of selling energy in the balancing market at a high price. On the other hand, in case 3 where the expected imbalance price is high, both risk-neutral and risk-averse producers tend to increase the day-ahead market price. Therefore, the risk-neutral can increase its profit in a higher day-ahead price. In addition, this producer reduces its share in the day-ahead market with the hope of selling energy in the balancing market at a high price. (Fig. 4).

![Fig. 4. Impact of imbalance price on wind power in the DA market](image)

The participation of the wind power producer in the balancing market for various imbalance prices is shown in

![Fig. 5. Participation of wind power producer in the balancing market](image)
Table VI. The strategic behavior of the producer is obvious, where in both risk levels it has to buy significant energy in case 1 while it has a substantial sale share in case 3.

<table>
<thead>
<tr>
<th></th>
<th>0.95% Imb. price</th>
<th>Imb. price</th>
<th>1.05% Imb. price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rho=0</td>
<td>-696</td>
<td>-366</td>
<td>1283</td>
</tr>
<tr>
<td>Rho=10</td>
<td>-696</td>
<td>1283</td>
<td>4726</td>
</tr>
</tbody>
</table>

In addition, the total demand cleared in different imbalance prices are shown in Fig. 5. Imbalance prices affects the total demand scheduled in the day-ahead market, where higher imbalance prices lead to a falling trend in the demand served.

![Graph](image)

Fig. 5. Impact of imbalance price on demand scheduled in the DA market

Finally, the impact of imbalance prices on the total DR procurement by the wind power producer is given in Table VII. The producer in both risk levels for case 1 is not willing to buy DR and thus, offers a low DR price to the aggregator (i.e., $27.44/MWh). On the other hand, both risk-neutral and risk-averse producers buy significant DR in high imbalance prices to cope with the risk of the balancing market (Case 3). To this end, they offer $31/MW to the DR aggregator and obtain 500 and 450 MW DR respectively.

Table VII. Impact of the imbalance price on DR procurement by the wind power producer (MW, $/MW)

<table>
<thead>
<tr>
<th></th>
<th>0.95% Imb. price</th>
<th>Imb. price</th>
<th>1.05% Imb. price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rho=0</td>
<td>0 27.44 0</td>
<td>27.4 500</td>
<td>31</td>
</tr>
<tr>
<td>Rho=10</td>
<td>0 27.44 500</td>
<td>31</td>
<td>450 31</td>
</tr>
</tbody>
</table>

VI. CONCLUSIONS

This paper considers a wind power producer with market power in the day-ahead market. An energy offering strategy is proposed through which the strategic wind power producer purchases demand response (DR) from a DR aggregator. The problem is formulated using a bilevel approach, where the upper-level represents the wind producer profit maximization while the lower-level problems respectively model the day-ahead market clearing process and the DR aggregator behavior. The problem is then transformed into a linear approach through proper techniques.

The overall problem is solved using stochastic programming in which the risk is carried out using CVaR. It is assessed on a case of the Nordic Market. The main findings are as follows. 1) A strategic wind power producer affects the market by using its market power to fix the market price. 2) A risk-neutral producer plays strategically to increase its profit in the day-ahead market while the risk-averse producer uses its market power in such a way to compensate possible deviations in the balancing market. In addition, the risk-averse producer tends to employ more DR for this purpose. 3) Imbalance prices have a significant impact on the behavior of a strategic wind producer in the market as well as DR procurement.

VII. APPENDIX

A. KKT optimality conditions

The Lagrangian function of each lower-level problem is differentiated with respect to the relevant variables to derive its KKT optimality conditions. In addition, the complementarity slackness conditions obtained from these KKT conditions are linearized using Fortuny-Amat approach [17]. Expressions (A1)-(A20) shows the corresponding derivatives for lower-level problem 1.

\[ \lambda^{W,of}(wu, t) - \lambda^{DA}(t) + t^{Max}(wu, t) - t^{Min}(wu, t) = 0 \]  
\[ \forall wu, \forall t \]  
\[ \lambda^{G}(gu, b, t) - \lambda^{DA}(t) + \alpha^{Max}(gu, b, t) - \alpha^{Min}(gu, b, t) = 0 \]  
\[ \forall gu, \forall b, \forall t \]  
\[ \lambda^{DR,DA}(dru, t) - \lambda^{DA}(t) + \theta^{Max}(dru, dt) - \theta^{Min}(dru, t) = 0 \]  
\[ \forall dru, \forall t \]  
\[ \lambda^{DA}(t) - \lambda^{D}(du, db, t) + \phi^{Max}(du, db, t) \]  
\[ \forall du, \forall db, \forall t \]  
\[ 0 \leq t^{Max}(wu, t) \leq M^{Max} t^{W, max}(wu, t), \forall wu, \forall t \]  
\[ 0 \leq P^{W,of}(wu, t) - P^{WDA}(wu, t) \leq M^{Max} (1 - v^{W, max}(wu, t)) \]  
\[ \forall wu, \forall t \]  
\[ 0 \leq t^{Min}(wu, t) \leq M^{Min} t^{W, min}(wu, t), \forall wu, \forall t \]  
\[ 0 \leq P^{WDA}(wu, t) - M^{Min} (1 - v^{W, min}(wu, t)) \]  
\[ \forall wu, \forall t \]  
\[ 0 \leq \alpha^{Max}(gu, b, t) \leq M^{Max} \alpha^{G, max}(gu, b, t), \forall gu, \forall b, \forall t \]  
\[ 0 \leq P^{G, max}(gu, b, t) - P^{G}(gu, b, t) \leq M^{Max} (\alpha^{G, max}(gu, b, t))^{-1} \]  
\[ \forall gu, \forall b, \forall t \]  
\[ 0 \leq \alpha^{Min}(gu, b, t) \leq M^{Min} \alpha^{G, min}(gu, b, t), \forall gu, \forall b, \forall t \]  
\[ 0 \leq P^{G}(gu, b, t) - M^{Min} (1 - \alpha^{G, min}(gu, b, t)) \]  
\[ \forall gu, \forall b, \forall t \]  
\[ 0 \leq \theta^{Max}(dru, t) \leq M^{Max} \theta^{DR, max}(dru, t), \forall dru, \forall t \]  
\[ 0 \leq P^{DR,DA}(dru, t) - P^{DR}(dru, t) \leq M^{Max} (\theta^{DR, max}(dru, ))^{-1} \]  
\[ \forall dru, \forall t \]
\begin{align}
0 & \leq \theta^\text{Min}(du,t) \leq M^\text{Min}_\theta \nu^\text{DR,min}(du,t), \forall du, \forall t \\
0 & \leq P^\text{DR,DA}(du,t) \leq M^\text{Min}_\theta (1 - \nu^\text{DR,min}(du,t)), \forall du, \forall t
\end{align}

(15)

(16)

\begin{align}
0 & \leq \varphi^\text{Max}(du,db,t) \leq M^\text{Max}_\varphi \nu^\text{DR,max}(du,db,t) \\
0 & \leq \varphi^\text{Min}(du,db,t) \leq M^\text{Min}_\varphi \nu^\text{DR,min}(du,db,t) \\
0 & \leq P^\text{D}(du,db,t) \leq M^\text{Min}_\theta (1 - \nu^\text{DR,min}(du,db,t))
\end{align}

(17)

(18)

(19)

(20)

The KKT conditions of lower-level problem 2 are shown in (A21)-(A26):

\begin{align}
- \sum_{s \in \Omega_s} \pi(s) \times C^{\text{DR,T}}(t) \times \lambda^\text{DR}(t) - \gamma(t,s) - \mu^W(t,s) = 0, \forall s, t
\end{align}

(A21)

\begin{align}
- \sum_{s \in \Omega_s} \pi(s) \times C^{\text{DR,T}}(t) \times \lambda^C(c,t,s) - \gamma(t,s) - \mu^C(c,t,s) = 0
\end{align}

(A22)

\begin{align}
0 & \leq sp^W(t,s) \leq M^\text{SP} \times \nu^W(t,s), \forall s, \forall t
\end{align}

(A23)

\begin{align}
0 & \leq sp^C(c,t,s) \leq M^\text{SP} \times \nu^C(c,t,s), \forall c, \forall s, \forall t
\end{align}

(A24)

\begin{align}
0 & \leq \mu^W(t,s) \leq M^\mu \times (1 - \nu^W(t,s)), \forall s, \forall t
\end{align}

(A25)

\begin{align}
0 & \leq \mu^C(c,t,s) \leq M^\mu \times (1 - \nu^C(c,t,s)), \forall c, \forall s, \forall t
\end{align}

(A26)

Note that \( M(\cdot) \) parameters in all the above equations are sufficiently large constants and \( \nu(\cdot) \) variables are binary variables.

\section*{B. Strong duality theorem}

The strong duality theorem is used to extract the linear formulation of the product of \( P^{WDA}(du,t) \times \lambda^DA(t) \) as well as \( P^D(t) \times \lambda^DR(t) \). According to the strong duality theorem, the values of primal objective function and the dual function must be equal at the optimal solution [16].

\textbf{Lower-level problem 1:} The primal problem (\textit{MinusSW} from Eq. (10)) is equal to its dual (right hand side) as follows.

\textit{MinusSW} = \( \sum_{wae\in\text{WU}} P^{WOF}(wu,t) \times \tau^\text{Max}(wu,t) \)

\begin{align}
- \sum_{wu\in\text{WU}} P^{WOF}(wu,t) \times \tau^\text{Max}(wu,t)
& \leq \sum_{wu\in\text{WU}} P^{WDA}(wu,t) \times \lambda^DA(t) \\
& \leq - \sum_{wu\in\text{WU}} P^{WOF}(wu,t) \times \tau^\text{Max}(wu,t), \forall t
\end{align}

(A28)

Thus, substituting the above term in the primal problem (\textit{MinusSW}) and simplifying it, the linear form of the product of \( P^{WDA}(du,t) \times \lambda^DA(t) \) is given as:

\begin{align}
& - \sum_{wu\in\text{WU}} P^{WDA}(wu,t) \times \lambda^DA(t) = \\
& - \sum_{wu\in\text{WU}} P^{WOF}(wu,t) \times \tau^\text{Max}(wu,t), \forall t
\end{align}

(A29)

\textbf{Lower-level problem 2:} Similarly, we have the primal problem (\textit{MinusDR_R} from Eq. (16)) equal to its dual (right hand side) as follows:

\begin{align}
& \sum_{s \in \Omega_s} \pi(s) \times \gamma(t,s) = - \sum_{s \in \Omega_s} \pi(s) \times C^{\text{DR,T}}(t) \times \\
& sp^W(t,s) \times \lambda^\text{DR}(t) + \sum_{c \in C} sp^C(c,t,s) \times \lambda^C(c,t,s)
\end{align}

(A30)

Given the above duality and also from Eq. (9), the product of \( P^D(t) \times \lambda^DR(t) \) is easily obtained as follows.

\begin{align}
p^D(t) \times \lambda^DR(t) = - \sum_{s \in \Omega_s} \pi(s) \times \gamma(t,s) \\
- \sum_{s \in \Omega_s} \pi(s) \times C^{\text{DR,T}}(t) \times \sum_{c \in C} sp^C(c,t,s) \times \lambda^C(c,t,s), \forall t
\end{align}

(A31)

\section*{REFERENCES}


Demand Response Application in an Electricity Market Integrating Wind and PV Resources

Nadali Mahmoudi, Student Member, IEEE, Tapan K. Saha, Senior Member, IEEE

Abstract—Renewable energy resources are increasingly growing around the world where wind and solar power are predominant. Apart from many advantages that these resources bring to power systems, they pose some significant challenges as well. Wind power is intermittent and non-dispatchable. This is even worse for solar power resources, when they mainly tend to be in small-scale systems such as roof-top PVs, which are beyond the control for an Independent System Operator (ISO). Thus ISOs need to explore new ways to cope with these issues. This paper proposes a market clearing problem from an ISO’s point of view. The ISO clears the energy and reserve markets while taking into account the uncertainty of wind power in the supply side and PV in the demand side. Additionally, the ISO is enabled to use demand response (DR) to alleviate the renewable intermittency. To this end, a DR aggregator is considered with the permission of participating in the reserve market. The proposed problem is evaluated on a test case and also the IEEE RTS system, where wind and PV data fed to this system are obtained from the Australian National Electricity Market (NEM).

Index Terms—Demand response, energy and reserve market clearing, ISO, roof-top PV, wind power.

NOMENCLATURE

A. Indices

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
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<tbody>
<tr>
<td>dru</td>
<td>Index for DR units (dru = 1: N_{dru})</td>
</tr>
<tr>
<td>l</td>
<td>Index for loads (l = 1: N_l)</td>
</tr>
<tr>
<td>g</td>
<td>Index for generator (g = 1: N_g)</td>
</tr>
<tr>
<td>w</td>
<td>Index for scenarios (w = 1: N_w)</td>
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<tr>
<td>wp</td>
<td>Index for wind producers (wp = 1: N_{wp})</td>
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B. Constants

<table>
<thead>
<tr>
<th>Symbol</th>
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<tbody>
<tr>
<td>B_{nr}</td>
<td>Susceptance of line nr</td>
</tr>
<tr>
<td>C_{D,DR}</td>
<td>Cost offer of demand response unit dru for down</td>
</tr>
<tr>
<td>C_{U,DR}</td>
<td>Cost offer of demand response unit dru for up</td>
</tr>
<tr>
<td>C_g</td>
<td>Cost offer of generator g</td>
</tr>
<tr>
<td>C_D</td>
<td>Cost offer of generator g for downward regulation</td>
</tr>
<tr>
<td>C_U</td>
<td>Cost offer of generator g for upward regulation</td>
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</tbody>
</table>

C. Variables

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>L_{Shed}</td>
<td>Load shedding for load l</td>
</tr>
<tr>
<td>p_g</td>
<td>Power scheduled for generator g</td>
</tr>
<tr>
<td>p_{wp}</td>
<td>Power scheduled for wind producer wp</td>
</tr>
<tr>
<td>p_{spill}</td>
<td>Wind spillage of wind producer wp in scenario w</td>
</tr>
<tr>
<td>r_{D,DR}</td>
<td>Downward reserve by demand response unit dru in</td>
</tr>
<tr>
<td>r_{U,DR}</td>
<td>Upward reserve by demand response unit dru in</td>
</tr>
<tr>
<td>r_g</td>
<td>Downward reserve by generator g in scenario w</td>
</tr>
<tr>
<td>r_u</td>
<td>Upward reserve by generator g in scenario w</td>
</tr>
<tr>
<td>\lambda_n</td>
<td>Locational marginal price at node n</td>
</tr>
<tr>
<td>\delta_n^0</td>
<td>Voltage angle at node n in the day-ahead market dispatch</td>
</tr>
<tr>
<td>\delta_{nw}</td>
<td>Voltage angle at node n in the reserve market in scenario w</td>
</tr>
</tbody>
</table>

Authors are with the School of Information Technology and Electrical Engineering, the University of Queensland, Brisbane, Australia (emails: n.mahmoudi@uq.edu.au, saha@itee.uq.edu.au, m.eghbal@uq.edu.au).
I. INTRODUCTION

RENEWABLE energy growth is expected to continue with a rapid pace in near future. Wind power is dominant among all renewable resources, where in some countries such as Denmark and Germany it is becoming matured enough. Solar PV penetration has also been significantly increasing in many countries. This increasing trend in solar power is mainly due to roof-top based small-scale PV units installed by electricity consumers.

High penetrations of such renewable resources bring some challenges to the electricity market. Wind power, usually in a large scale, is uncertain and non-dispatchable. The good thing however is that as wind penetration becomes significant, it is expected to be treated as similar to conventional power plants. This way, wind power producers have to participate in the market while compensating their power imbalances. Note that this is currently practiced for some wind power producers in electricity markets such as Western Denmark [1], Germany and Australia [2]. This observation is not valid for PV power, where it is usually in the demand side. Indeed, PV power imposes uncertainty to demand, which causes more difficulties in the market dispatch carried out by ISOs.

Investigations are underway to resolve the above issues. A review of the literature indicates the majority of the study is dedicated to the wind related problems and their proposed solutions. The joint operation of wind and controllable resources such as pump-storage systems, hydro power plants, battery storage units and demand response (DR) are provided as a solution for alleviating wind intermittency, mainly from wind power producers’ perspective [3-7]. Wind integration from an ISO point of view is modelled in some studies as in [8-14]. Authors in [8] assess the level of wind penetration in the Portuguese system while using flexible backup production. Authors in [9-11] indicate that applying real-time pricing schemes result in a higher utilization of wind production and a lower cost of the system. The reserve requirement for a system integrating wind power production is addressed in [12]. Pool pricing for such a system is presented in [13]. Authors in [14] evaluate the impact of DR on the generation mix of a system integrating wind power. The studies on PV are not as many as that of wind incorporation. A solar-powered micro-grid is studied in [15] where its pricing mechanism is proposed. A model for participating concentrating solar power in the market is proposed in [16], where the unit can use storage to increase its revenue. Economic impacts of solar power on the PJM electricity market are analysed in [17]. There has been no investigation which explicitly studied a system integrating both PV (small units) and wind power production while employing DR for easing their intermittency.

This paper considers an electricity market integrating wind and solar power. To this end, a single-period auction including energy and reserve markets is taken into account. In this context, wind power producers play like conventional power plants, with an exception that they may only be capable of doing reserve down in the market. Additionally, plausible realizations of wind power production are taken into account to address the wind power uncertainty. On the other hand, load comprises three parts. The majority of the load is considered as an inelastic demand to be supplied in the energy market. PV power production is represented as a negative load deducted from the original load. PV power is intermittent which is modelled as an uncertainty of the demand side. Finally, a limited specific portion of the load is considered to be elastic. A DR aggregator is proposed, which is responsible for this elastic load. The DR aggregator indeed enrolls in the reserve market as a regulation up/down provider. The overall problem is formulated as a stochastic market dispatch problem carried out by an ISO. The problem is evaluated on a test case and also the IEEE RTS 24 bus system. PV and wind power for this system are modelled from the Australian NEM realistic data.

The contributions of the paper are as follows.

- A market model integrating both wind and PV resources is proposed in which their corresponding intermittency in the supply and demand sides is taken into account.
- In order to help the ISO to lessen the renewable production uncertainty, a DR aggregator is proposed, which provides upward and downward regulation in the reserve market.

The rest of the paper is structured as follows. Section II discusses the proposed market model and provides its problem formulation. The case study and results are explained in section III. Section IV concludes the paper.

II. THE PROPOSED MODEL

The proposed model studies a single-period market, which is rather similar to the market dispatch presented in [13] than the security constrained unit commitment analysed in [18]. The model decides on the energy dispatch and reserve deployment. Indeed, energy decisions are made on the day prior to the market dispatch while those of the reserve market are cleared at real time. The following procedure is used in the proposed model.

Conventional power plants place their offer in the market while determining the maximum ramp up and ramp down that they can provide in the reserve market. The spinning reserve market is only modelled in the paper. Nevertheless, non-spinning reserves can be included in the model with some modifications. The cost associated with these power plants is given in (1). In addition, the size limit of the scheduled power of generating unit \( g \) in the day-ahead market is enforced in (2). This limit for upward and downward regulation is posed in (3) and (4), respectively. Finally, constraint (5) ensures the total participation of the power plant does not exceed its maximum capacity.

\[
C_g P_g + C_g^U f_{g,w}^U - C_g^D f_{g,w}^D \leq 0 \leq P_g \leq P_g^{Max} \tag{1}
\]

\[
0 \leq f_{g,w}^U \leq R_{g}^{U,Max} \tag{2}
\]

\[
0 \leq f_{g,w}^D \leq R_{g}^{D,Max} \tag{3}
\]

\[
0 \leq P_g + f_{g,w}^U - f_{g,w}^D \leq P_g^{Max} \tag{4}
\]
Wind power producers are also able to offer their energy in the market. However, these producers can only make regulation down in the reserve market. This is indeed the current practice for some semi-scheduled wind power producers in the Australian National Electricity Market [19]. In addition, similar to [13], the cost of downward regulation is assumed to be identical to the cost offer of the producer in the market. The cost function corresponding to the offer of wind power producer wp is calculated as follows.

\[ C_{wp}\left(P_{wp} - P_{spill}\right) \]  \hspace{1cm} (6)

The wind spillage (downward regulation reserve by the wind power producer) is:

\[ P_{spill}^{wp} = P_{total}^{wp} - P_{wp}^{S} \]  \hspace{1cm} (7)

Substituting (7) in (6), and since the term \( C_{wp} P_{total}^{wp} \) is constant, the cost term of (6) can be simplified as follows.

\[ -C_{wp} P_{spill}^{wp} \]  \hspace{1cm} (8)

\[ 0 \leq P_{wp}^{S} \leq P_{Exp}^{Spec} \]  \hspace{1cm} (9)

\[ 0 \leq P_{spill}^{wp} \leq P_{wp}^{S} \]  \hspace{1cm} (10)

Constraints (9) and (10) respectively impose the power scheduled in the day-ahead market and the spilled wind power at real time.

On the other hand, demand is considered to be mainly inelastic. Small-scale PV systems such as rooftop PV are taken into account as the negative load. These systems have widely been used in Australia, particularly in the states of Queensland and South Australia. Some serious issues that they have brought to the power system are voltage fluctuations, power quality problems and market clearing issues. Of course, this paper’s concern is on the market related problems. Fig. 1 indicates a typical weekly load profile of South Australia (SA) for a summer season (14-20 Jan 2013). It is obvious how PV production affects the load shape during the day. Additionally, the uncertainty of PV is noticeable, where for instance PV production in some periods such as the first day is significant while in others like the fourth day is small. This change and uncertainty may cause the shutdown of some power plants and in the worst case, wind power spillage. This is an obvious disadvantage since huge subsidies are spent to increase wind power penetration while the market operator has to spill part of wind power as a result of PV production. For this reason, demand response (DR) is included as a solution. To this end, DR aggregators are allowed to enrol in the reserve market. They can provide both types of reserves, i.e. upward and downward. Indeed, in the upward regulation they ask their customers to reduce their load while in the downward regulation they encourage consumers to consume more energy.

Overall the load model is formulated in (11).

\[ L_{t,w}^{Net} = L_{t}^{Orgl} - P_{t,w}^{PV} \]  \hspace{1cm} (11)

![Fig. 1. Original vs. net load profile (SA, 14-22 Jan 2013)](image)

We assume that the part of the load which is inelastic has to be scheduled in the day-ahead market and it is derived as follows.

\[ L_{t}^{S} = L_{t}^{Orgl} - \sum_{w=1}^{N_{wp}} \pi(w) P_{t,w}^{PV} \]  \hspace{1cm} (12)

Thus, the cost term in the proposed market dispatch is indeed the cost of load shedding, shown in (13). The maximum load shedding is constrained in (14).

\[ VolL_{t}^{Shed} \]  \hspace{1cm} (13)

\[ 0 \leq L_{t,w}^{Shed} \leq L_{t,w}^{S} \]  \hspace{1cm} (14)

Finally, the cost related to the participation of DR in the reserve market is illustrated in (15). In addition, the sizes of regulation up and down are restricted in (16) and (17), respectively.

\[ C_{dru}^{U,DR} - C_{dru}^{D,DR} \leq C_{dru}^{D,DR} - C_{dru}^{U,DR} \]  \hspace{1cm} (15)

\[ 0 \leq L_{dru,w}^{U,DR} \leq R_{dru,w}^{U,DR} \]  \hspace{1cm} (16)

\[ 0 \leq L_{dru,w}^{D,DR} \leq R_{dru,w}^{D,DR} \]  \hspace{1cm} (17)

The ISO aims at maximizing social welfare or minimizing the system cost. Since this paper assumes that the majority of load is inelastic, the latter objective is used here.

\[ Min \sum_{w=1}^{N_{wp}} \pi(w) \left( \sum_{g=1}^{N_{g}} C_{g} P_{g} + C_{g}^{U,U} r_{g,w}^{U,DR} - C_{g}^{D,D} r_{g,w}^{D,DR} \right) \]

\[ + \sum_{dru=1}^{N_{dru}} C_{dru}^{U,DR} - C_{dru}^{D,DR} \right) \]

\[ - \sum_{w=1}^{N_{wp}} C_{wp} P_{wp,w}^{spill} \]

\[ + \sum_{l=1}^{N_{l}} VolL_{l}^{Shed} \]

subject to

\[ \sum_{g|M(g,n)=1} P_{g} + \sum_{wp|M(wp,n)=1} P_{wp}^{S} - \sum_{l|M(l,n)=1} L_{l,w}^{S} = \sum_{r|M(r,n)=1} B_{wp} \delta_{r}^{0} \delta_{r}^{0} \forall n : (\lambda_{n}) \]

(19)
\[ \sum_{\delta M_{(g,n)}=1}^U r_{g,w} - r_{g,w}^{D} + \sum_{L_{(l,n)}=1}^{wp} (P_{wp,w}^{total} - P_{wp,w}^{S} - P_{wp,w}^{spill}) \]

\[ - \sum_{\delta M_{(l,n)}=1}^{L_{l,w}} (L_{l,w}^{Net} - L_{l,w}^{Shed}) + \sum_{\delta M_{(l,n)}=1}^{D_{l,w}} L_{l,w}^{DR} - r_{l,w}^{D,DR} \]

\[ = \sum_{\delta M_{(r,n)}=1}^{B_{nr}} B_{nr}(\delta_{nw} - \delta_{rw} - \delta_{nw}^{(0)} + \delta_{nr}^{(0)}) \forall n, w \]

\[ B_{nr}(\delta_{nw} - \delta_{rw}) \leq C_{L_{Line}}^{nr} \] (21)

\[ B_{nr}(\delta_{nw} - \delta_{rw}) \leq C_{L_{Line}}^{nr} \] (22)

Constraints for generators: (2)-(5)

Constraints for wind power producers: (9)-(10)

Constraints for load shedding: (14)

Constraints for demand response: (16)-(17)

The objective function comprises the expected cost of conventional power plants in both energy and reserve markets, and the expected cost of demand response, wind spillage and load shedding, all in the reserve market. Constraint (19) represents the power balance in the day-ahead market dispatch at each node. Note that the network losses are disregarded here while the model considers a DC power flow. Constraint (20) indicates the power balance enforcement in the reserve market. Constraints (21) and (22) impose the line capacity limit. The remaining constraints are explained earlier. The overall problem is a stochastic mixed-integer programming approach. CPLEX 11.1.1 under GAMS [20] is used to solve this problem.

III. CASE STUDY

A. Three Bus System

A three-bus system is considered to assess the proposed problem. The information of this system is as follows [13]. The data for conventional power plants and demand response is provided in Table I. It is assumed that the cost of reserve by conventional power plants is identical to the cost of their power production [13]. In addition, the uncertainty of wind and PV power is represented by three scenarios each, overall 9 scenarios (Table II). The capacity of each line is limited by 100MW while the line reactance is 0.13 p.u. Note that for the sake of simplicity, network losses are neglected here. The original load located at bus 3 is 200 MW with the assumed VOLL of $1000. In addition, we assume that the wind power producer places its offer price at zero. Moreover, maximum wind offer in the market is restricted by the expected wind power scenarios in Table II, i.e. 30.5MW. Finally note that, the amount of load to be scheduled in the day-ahead market is obtained from Eq. (12).

![Diagram of Three-Bus System](image)

**Table I**

<table>
<thead>
<tr>
<th>Generator Data</th>
<th>Max Power (MW)</th>
<th>Offer Cost ($/MWh)</th>
<th>Upward Cost ($/MWh)</th>
<th>Downward Cost ($/MWh)</th>
<th>Max Upward Power (MW)</th>
<th>Max Downward Power (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>G1</td>
<td>100</td>
<td>20</td>
<td>20</td>
<td>20</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>G2</td>
<td>50</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td>G3</td>
<td>100</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td>DR</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

**Table II**

<table>
<thead>
<tr>
<th>WIND AND PV POWER SCENARIOS (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario</td>
</tr>
<tr>
<td>PV</td>
</tr>
<tr>
<td>Wind Probability of each scenario</td>
</tr>
</tbody>
</table>

**Table III**

<table>
<thead>
<tr>
<th>STUDIED CASES WITH VARIOUS RESOURCES INTEGRATION (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case</td>
</tr>
<tr>
<td>C0</td>
</tr>
<tr>
<td>C1</td>
</tr>
<tr>
<td>C2</td>
</tr>
<tr>
<td>C3</td>
</tr>
<tr>
<td>C4</td>
</tr>
<tr>
<td>C5</td>
</tr>
<tr>
<td>C6</td>
</tr>
<tr>
<td>C7</td>
</tr>
<tr>
<td>C8</td>
</tr>
<tr>
<td>C9</td>
</tr>
</tbody>
</table>

The cases provided in Table III are as follows.

- **C0**: the system integrates neither DR nor renewable energy resources.

Fig. 2. Three-bus system

The DR capacity (Table I) as well as PV and wind power productions in Table II is considered as the base case. Consequently, six distinct cases are determined according to the base case (See Table III). Note that the values represented for each resource, i.e. DR, PV and wind, indicates the percentage of the base case. Note also that the maximum wind offer also changes accordingly. Finally, it should be emphasized that the uncertainty of PV and wind power increases as the level of their penetration grows in the given cases.
• C1: the system only has PV and wind. While wind production is identical to the base case, the PV penetration increases up to three times of the base PV production.
• C2: this case is similar to C1, but it includes DR as well.
• C3: this case simultaneously studies the high penetration of wind and PV production while no DR is modelled.
• C4: C3 is studied while DR is added to the system.
• C5: this case is similar to C4, but it models the impact of an increasing DR penetration level.

Fig. 3 displays the cost of the system for different cases. The following observations are made from the cost trend. First, it is obvious that integrating wind and PV resources reduces the cost of the system (C0 vs. C1). In addition, introducing a higher penetration level of PV in the demand side leads to a decreasing cost of the system (See C1). This reduction is even higher with the application of demand response along with using PV (C2). One interesting result is that increasing the level of both wind and PV production is costly for the system (C3). In the worst case, the cost of the system in comparison with the base case increases by around 40% when the wind and PV penetration is three times than the base case. This cost is alleviated when DR is used in the system (See C4). However, there is still an increasing trend for the system cost with regards to high levels of PV and wind production. This issue could be resolved when the DR capacity increases (C5). The reasons behind all changing trends are discussed in following by giving more results.

Table IV compares the wind spillage in different cases for individual scenarios. No wind spillage is observed in the first four scenarios. These scenarios indeed coincide with low and partly medium wind power scenarios in Table II. The main findings from Table IV are as follows. The increasing penetration of PV production in the demand side causes more wind spillage. Ultimately, in C1-5 where the PV production is three times, wind is spilled 14.5 and 29.5 MW in scenarios 6 and 9, respectively. That means the overall spillage of around 4.4 MW in C1-5. The ISO can reduce this cut using DR (C2). However, there still exists wind spillage in scenario 9 of C2-4 and C2-5, where the PV penetration is considerably high. It is obvious that increasing wind and PV penetration simultaneously leads higher wind spillage (C3). C3-4, where there is the highest wind and PV integration, results in 21 MW wind cut. This is just under five times greater than wind spillage in C1-5, where the wind penetration is one third. That is, the wind spillage does not follow a linear proportion of wind production increment. Similar to case 2, introducing DR eases the wind spillage and increasing its potential can even help more to this end (C2 & C5).

Table V illustrates how DR is able to facilitate both load shedding and wind spillage. Note that, regulations up and down are shown by ‘U’ and ‘D’, respectively. Note also that regulation up means that the DR aggregator exercise load reduction programs while in regulation down it encourages consumers to consume more energy. Consider scenarios 1 and 2 (w1 and w2) only. Note that the load is entirely supplied in other cases. The results indicate that load shedding in C3-2 is around 11 MW (only w1), while it is approximately 27 and 53 MW for C3-3 and C3-4, respectively. With applying the probability of these scenarios, i.e. 0.1, these values respectively come to 1.1, 2.7 and 5.3 MW load shedding in the mentioned cases. Indeed, these amounts of load shedding bring a high cost to the system as shown in Fig. 3. Case 4 illustrates that employing DR by the ISO lessen the severity of load shedding. C4-2 has no load shedding while C4-3 and C4-
The wind power scheduled in the energy market is shown in Fig. 5. The results obviously indicate a decreasing trend in the accepted offers of generators when the penetration of PV and wind production increases. This is reasonable since on one hand PV integration reduces the net load and on the other hand, wind production is cheap and thus the ISO can reduce the system cost by using this resource. Another observation interpreted from Fig. 5 is that DR slightly changes (small reduction) the scheduled power of conventional power plants.

The wind power scheduled in the energy market is illustrated in Table VI. The ISO indeed dispatches the maximum expected power of the wind power producer. This is sensible since the energy offer price of wind power is placed at zero.
Table VII represents the downward reserve deployed from generator 2 in scenarios 5-9 (w5-w9). Note that no downward reserve is procured from generator 3. The ISO does not require this reserve when there is no renewable production (C0). However, the integration of PV and wind urges the deployment of the downward reserve from generator 2. This is mainly because of the fluctuation between the dispatched wind power and load scheduled in the day-ahead market and their real-time amounts. The results also illustrate that the need for downward reserve decreases as DR is introduced in the system (See C2 and C5). In addition, a higher wind production results in the same way (C2 vs. C4).

<table>
<thead>
<tr>
<th>Table VII</th>
<th>DOWNWARD RESERVE FROM GENERATOR (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Upward w5 w6 w7 w8 w9</td>
</tr>
<tr>
<td>C0-1</td>
<td>0 0 0 0 0</td>
</tr>
<tr>
<td>C1-1</td>
<td>4.5 14.5 9.5 19.5 20</td>
</tr>
<tr>
<td>C1-2</td>
<td>4.5 19.5 4.5 19.5 20</td>
</tr>
<tr>
<td>C1-3</td>
<td>4.5 20 0 19.5 20</td>
</tr>
<tr>
<td>C1-4</td>
<td>4.5 20 0 19.5 20</td>
</tr>
<tr>
<td>C1-5</td>
<td>4.5 20 0 19.5 20</td>
</tr>
<tr>
<td>C2-1</td>
<td>0 0 0 0 9.5</td>
</tr>
<tr>
<td>C2-2</td>
<td>0 0 0 0 14.5</td>
</tr>
<tr>
<td>C2-3</td>
<td>0 4.5 0 0 19.5</td>
</tr>
<tr>
<td>C2-4</td>
<td>0 9.5 0 0 19.5</td>
</tr>
<tr>
<td>C2-5</td>
<td>0 14.5 0 0 14.5</td>
</tr>
<tr>
<td>C3-1</td>
<td>6.75 20 14.25 20 20</td>
</tr>
<tr>
<td>C3-2</td>
<td>0 0 0 0 0</td>
</tr>
<tr>
<td>C3-3</td>
<td>0 0 0 0 0</td>
</tr>
<tr>
<td>C3-4</td>
<td>0 0 0 0 0</td>
</tr>
<tr>
<td>C4-1</td>
<td>0 1.75 0 9.25 20</td>
</tr>
<tr>
<td>C4-2</td>
<td>0 0 0 0 0</td>
</tr>
<tr>
<td>C4-3</td>
<td>0 0 0 0 0</td>
</tr>
<tr>
<td>C4-4</td>
<td>0 0 0 0 0</td>
</tr>
<tr>
<td>C5-1</td>
<td>0 0 0 0 0</td>
</tr>
<tr>
<td>C5-2</td>
<td>0 0 0 0 0</td>
</tr>
<tr>
<td>C5-3</td>
<td>0 0 0 0 0</td>
</tr>
</tbody>
</table>

B. IEEE RTS System

The proposed problem is also studied on the IEEE 24-bus system [21]. The simulation is done for one period, i.e. 12pm. Two wind power producers are considered at buses 6 and 8. Each wind power producer is considered at the size of three times than the following wind farm. The wind farm Lake Bonney 2 in South Australia is chosen [22]. This wind farm is located at Mt Gambier AERO and its installed capacity is 159MW (53 of Vestas 3MW Turbines). Wind speed scenarios are generated using the ARMA model where the summer season data from 2007-2012 is used as input time series. Twenty wind speed scenarios are generated for each site. The median wind power for this wind farm is 45 MW. Five PV units are considered at buses 5, 6, 8, 15, 18, 20. Ten PV power scenarios are simply considered where each scenario coincides with PV production in South Australia at 12pm. Overall 200 scenarios are generated with the identical probability. Note that PV production is rescaled based on the IEEE system to represents 10% of total load at the relevant buses. DR aggregators are assumed to present their offers at buses 5, 6, 8, 15, 18. The cost offers of the DR aggregators are chosen in such a way that they are close to the power plants at or near their corresponding buses. Note also that the above PV and wind production is considered as the base case here. Four main cases are designed accordingly (Table VIII).

<table>
<thead>
<tr>
<th>Table VIII</th>
<th>CASES CONSIDERED FOR STUDY ON THE IEEE RTS 24-BUS SYSTEM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case</td>
<td>DR</td>
</tr>
<tr>
<td>C0</td>
<td>0</td>
</tr>
<tr>
<td>C1</td>
<td>C1-1</td>
</tr>
<tr>
<td></td>
<td>C1-2</td>
</tr>
<tr>
<td>C2</td>
<td>C2-1</td>
</tr>
<tr>
<td></td>
<td>C2-2</td>
</tr>
<tr>
<td>C3</td>
<td>C3-1</td>
</tr>
</tbody>
</table>

The cost of the system for various cases is depicted in Fig. 7. The declining trend with respect to the higher integration of wind and PV power as well as the DR capacity confirms the results obtained from the 3 bus test case in Fig. 3. Note that the system has no load shedding in the studied cases and thus it is not faced with the cost spikes shown in the previous section.

Fig. 7. The cost of the IEEE 24-bus system

Power spillage for wind power producers 1 and 2 (WP1 & WP2) is provided in Table IX. The wind power spilled from the WP1 is significant while that of WP2 is low. In addition, it is obvious that integrating more PV leads to a higher level of wind spillage. This clearly shows the impact of PV and its production uncertainty on wind spillage in the market (Consider that there is no PV at WP2’s bus). Another observation is the impact of DR on the wind spillage. The results here also confirm the findings of the 3-bus case studied earlier.

<table>
<thead>
<tr>
<th>Table IX</th>
<th>WIND SPILLAGE FOR THE IEEE RTS 24-BUS SYSTEM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>WP1</td>
</tr>
<tr>
<td>C0-1</td>
<td>0</td>
</tr>
<tr>
<td>C1-1</td>
<td>49.5</td>
</tr>
<tr>
<td>C1-2</td>
<td>58.2</td>
</tr>
<tr>
<td>C2-1</td>
<td>38.5</td>
</tr>
<tr>
<td>C2-2</td>
<td>43.1</td>
</tr>
<tr>
<td>C3-1</td>
<td>33.4</td>
</tr>
</tbody>
</table>
Finally, the demand response deployed in the reserve market is displayed in Table X. The results summarize for the overall scenarios. Indeed, there are some scenarios in which the upward reserve is required while for others DR is called for the downward reserve. In addition, it is obvious that DR is mostly required to provide downward regulations at the buses which integrate wind power (dru2 and dru3). This is more apparent for dru3, where it provides downward reserve only.

<table>
<thead>
<tr>
<th>TABLE X</th>
<th>DR DEPLOYED IN THE RESERVE MARKET FOR THE IEEE RTS 24-BUS SYSTEM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reserve</td>
<td>dru1</td>
</tr>
<tr>
<td>C2-1</td>
<td>Upward</td>
</tr>
<tr>
<td></td>
<td>Downward</td>
</tr>
<tr>
<td>C2-2</td>
<td>Upward</td>
</tr>
<tr>
<td></td>
<td>Downward</td>
</tr>
<tr>
<td>C3-1</td>
<td>Upward</td>
</tr>
<tr>
<td></td>
<td>Downward</td>
</tr>
</tbody>
</table>

IV. CONCLUSIONS

This paper presents a market model for an ISO. This market integrates wind and PV power. In addition, DR is considered as a solution to resolve the issues related to the high level of wind and PV production. A DR aggregator is modelled, which is able to participate in the reserve market. The problem is formulated in a stochastic cost minimization from the ISO’s point of view. Plausible realizations of wind and PV power productions are applied to represent their uncertainty. The proposed method is solved in a test case and also the IEEE 24-bus system using GAMS 11.1.1 under GAMS. The main findings are as follows.

1- Integrating wind and PV production reduces the cost of the system. However, higher levels of penetration may pose a high cost to the system. This is mainly due to the fluctuation of renewable resources that causes load shedding in some cases.

2- Employing DR can reduce the cost of the system. In addition, it may lessen the severity of load shedding as a result of high renewable power penetration. Furthermore, DR is able to encourage consumers to consume more energy and consequently reduce wind spillage.

3- Increasing DR capacity for the systems with significant levels of renewable energy resources such as wind and PV has a major impact on controlling these resources fluctuation as well as reducing the cost of the system.

It should be emphasized that modelling a security-constrained unit commitment covering the whole 24 hours of the day of energy delivery makes our case stronger, where all technical aspects of power plants as well as load and DR are properly modelled. This study will indeed be presented in our future work.