

Bi-Level Optimization Considering Uncertainties of Wind
Power and Demand Response

A Dissertation Presented for the
Doctor of Philosophy
Degree

The University of Tennessee, Knoxville

Xin Fang

August 2016

Copyright © 2016 by Xin Fang

All rights reserved.

DEDICATION

This dissertation is dedicated to my beloved wife, Ningchao Gao, whose love, patience and encouragement make it possible for me to finish my Ph. D. study and this work.

ACKNOWLEDGEMENTS

I would like to express my thanks to those who helped me with various aspects of conducting research and writing this dissertation.

First and foremost, I would like to express my deepest gratitude to my major advisor, Dr. Fangxing Li for his continuous guidance and persistent help for this dissertation and all other research works during my Ph.D. study at the University of Tennessee at Knoxville (UTK). I am also grateful to Dr. Fangxing Li for funding my Ph.D. study.

I would like to thank Dr. Kevin Tomsovic, Dr. Kai Sun, and Dr. James Ostrowski for their time and efforts in serving as the members of my dissertation committee.

In addition, I would like to express my special thanks to Dr. Yanli Wei, Dr. Hao Huang, Dr. Zhiqiang Jin, Dr. Yao Xu, Dr. Qinran Hu, Dr. Xue Li, Mr. Haoyu Yuan, Mr. Hantao Cui, Mr. Linqun Bai, Mr. Can Huang, and Mr. Riyasat Azim for being supportive to my works as well as their kind advice in my course study and research. Also, I would like to thank all my friends and professors in the Center for Ultra-Wide-Area Resilient Electric Energy Transmission (CURENT) who create a loving and friendly atmosphere for conducting research.

Last but not least, this dissertation not only represents my work, but it is also a milestone representing four year of works at the University of Tennessee at Knoxville (UTK).

ABSTRACT

Recently, world-wide power systems have been undergone a paradigm change with increasing penetration of renewable energy. The renewable energy is clean with low operation cost while subject to significant variability and uncertainty. Therefore, integration of renewables presents various challenges in power systems. Meanwhile, to offset the uncertainty from renewables, demand response (DR) has gained considerable research interests because of DR's flexibility to mitigate the uncertainty from renewables. In this dissertation, various power system problems using bi-level optimization are investigated considering the uncertainties from wind power and demand response.

In power system planning, reactive power planning (RPP) under high-penetration wind power is studied in this dissertation. To properly model wind power uncertainty, a multi-scenario framework based on alternating current optimal power flow (ACOPF) considering the voltage stability constraint under the worst wind scenario and transmission N-1 contingency is developed. The objective of RPP in this work is to minimize the VAR investment and the expected generation cost. Benders decomposition is used to solve this model with an upper level problem for VAR allocation optimization and generation cost minimization as a lower problem.

Then, several problems related wind power and demand response uncertainties under power market operation are investigated. These include: an efficient and effective method to calculate the LMP intervals under wind uncertainty is proposed; the load serving entities' strategic bidding through a coupon-based demand response (CBDR) with which a load serving entity (LSE) may participate in the electricity market as strategic bidders by offering CBDR programs to customers; the impact of financial transmission right (FTR) with CBDR programs is

also studied from the perspective of LSEs; and the strategic scheduling of energy storages owned by LSEs considering the impact of charging and discharging on the bus LMP. In these problems, a bi-level optimization framework is presented with various objective functions representing different problems as the upper level problems and the ISO's economic dispatch (ED) as the lower level problem. The bi-level model is addressed with mathematic program with equilibrium constraints (MPEC) model and mixed-integer linear programming (MILP), which can be easily solved with the available optimization software tool.

Keywords: Bi-level optimization, power systems, wind power, demand response, electricity market, reactive power planning, strategic bidding, financial transmission right, energy storage.

TABLE OF CONTENTS

CHAPTER 1 INTRODUCTION	1
1.1 General Introduction	1
1.2 Dissertation Outline	2
1.3 Contributions.....	3
CHAPTER 2 REACTIVE POWER PLANNING CONSIDERING HIGH PENETRATION OF WIND POWER.....	5
2.1 Introduction.....	5
2.2 Wind Power Model.....	7
2.2.1 Correlated Wind Power Model	8
2.2.2 DFIG Reactive Power Capability	9
2.2.3 Wind Penetration	9
2.3 Problem Formulation	11
2.3.1 Nomenclature.....	11
2.3.2 RPP Model.....	12
2.3.3 Objective Function.....	13
2.3.4 Equality Constraints.....	14
2.3.5 Inequality Constraints	15
2.4 Problem Decomposition.....	16
2.4.1 Sub-problem.....	16
2.4.2 Master Problem.....	17
2.4.3 Benders Decomposition Procedure.....	19

2.5 Case study and results	20
2.5.1 IEEE 14-bus System Model	20
2.5.2 IEEE 118-Bus System	29
2.6 Conclusions	34
CHAPTER 3 EVALUATION OF LOCATIONAL MARGINAL PRICE INTERVALS CONSIDERING WIND POWER UNCERTAINTY	36
3.1 Introduction	36
3.2 LMP Interval and its Bi-level Optimization Form	37
3.3 Case Studies	40
3.3.1 PJM 5-bus System	40
3.3.2 IEEE 118-Bus System	41
3.4 Conclusion	42
CHAPTER 4 COUPON BASED DEMAND RESPONSE: A STRATEGIC BIDDING MODEL FOR LOAD SERVING ENTITIES	43
4.1 Introduction	43
4.2 Strategic Bidding Model for LSEs	46
4.2.1 Nomenclature	46
4.2.2 Procedure of LSEs' Strategic Bidding	47
4.2.3 Net Revenue of LSEs	49
4.2.4 ISO's Economic Dispatch	50
4.2.5 Bi-level Model of Strategic Bidding	51
4.3 Baseline Demand and Probabilistic Demand Reduction	52
4.3.1 Baseline Demand Model	52

4.3.2 Probabilistic Residential Demand Reduction Model	53
4.4 Mathematical Solution of the Proposed Model	57
4.4.1 Formulation as a MPEC.....	58
4.4.2 Mixed-integer Linear Programming (MILP)	58
4.4.3 Model Extensions to Integrate Wind Power	61
4.4.4 Demand Uncertainty under Different Coupon Prices	63
4.4.5 Overall Procedure	64
4.5 Case Studies	64
4.5.1 PJM 5-Bus Test System	65
4.5.2 Implication at Different Load Levels.....	65
4.5.3 Impact from Wind Power Capacity	69
4.5.4 Wind Power Forecast Uncertainty	70
4.5.5 IEEE 118-Bus System.....	72
4.6 Conclusions.....	76
CHAPTER 5 IMPACTS OF FTR ON LSE STRATEGIC BIDDING CONSIDERING COUPON BASED DEMAND RESPONSE	78
5.1 Introduction.....	78
5.2 Bidding Model for LSEs considering FTR and CBDR	82
5.2.1 Strategic Bidding in Deregulated Market	82
5.2.2 Revenue of LSEs considering FTR and CBDR.....	82
5.2.3 ISO's Market Clearing	84
5.2.4 Bi-level Model of LSE's Strategic Bidding.....	85
5.3 Baseline Demand and Probabilistic Demand Reduction	86

5.3.1 Baseline Demand Model.....	86
5.3.2 Probabilistic Demand Reduction Model.....	86
5.4 Mathematical Solution of the Proposed Model	87
5.4.1 Formulation of Single Level Optimization Model.....	88
5.4.2 Congestion Surplus	89
5.4.3 Mixed-integer Linear Programming (MILP) with FTR and CBDR	90
5.4.4 Integrating Uncertainty of Wind Power and CBDR	92
5.5 Case Studies	94
5.5.1 Illustrative Two-bus system.....	95
5.5.2 PJM 5-Bus Test System.....	96
5.5.3 IEEE 39-bus System	100
5.6 Conclusions.....	105
CHAPTER 6 STRATEGIC SCHEDULING OF ENERGY STORAGE FOR LOAD SERVING ENTITIES IN LMP MARKET	107
6.1 Introduction.....	107
6.2 Strategic Energy Storage Scheduling for LSEs	110
6.2.1 Net Revenue of Load Serving Entities considering ES	111
6.2.2 Traditional Scheduling of Energy Storage System.....	112
6.2.3 Bi-level Model for Strategic Scheduling of Energy Storage	113
6.2.4 Baseline Demand Model.....	115
6.3 Mathematical Solution of the Proposed Model	115
6.3.1 Formulation of an MPEC.....	116
6.3.2 Mixed-integer Linear Programming (MILP)	117

6.3.3 Model Extensions to Integrate Uncertainty	120
6.4 Case Studies	122
6.4.1 PJM 5-bus System.....	122
6.4.2 Comparison of Traditional Scheduling and Strategic Scheduling	123
6.4.3 IEEE 118-bus System	128
6.5 Conclusions.....	134
CHAPTER 7 CONCLUSION.....	135
7.1 Main Contributions and Conclusion	135
7.2 Future Research Work	136
LIST OF REFERENCES	139
APPENDIX.....	161
Publications during Ph.D. Study	162
Related Journal Papers	162
Conference Papers	163
VITA.....	165

LIST OF TABLES

Table 2.1 Unit Parameter of IEEE 14 Bus System	24
Table 2.2 The Worst Wind Scenarios under Different Cases	28
Table 2.3 VAR Allocation considering the VAR Cost.....	26
Table 2.4 VAR Allocation Considering the Total Cost.....	28
Table 2.5 No. of Iterations, CPU time and Wind Scenarios of Different Cases.....	28
Table 2.6 Wind Farms Data	29
Table 2.7 Unit Parameter of IEEE 118 Bus System	30
Table 2.8 Scenarios for Master Problem.....	31
Table 2.9 Impact of Scenario Reduction in Case a	32
Table 2.10 Impact of Scenario Reduction in Case b.....	33
Table 2.11 Impact of Scenario Reduction in Case c	33
Table 3.1 LMP interval results from MC method and the proposed method	41
Table 4.1 DR results under different operating points.....	67
Table 4.2 Parameters in Wind Uncertainty Test.....	71
Table 4.3 Load and Flat Electricity Rate on LSE Bidder's Buses.....	75
Table 4.4 Dispatched load on buses and LSE's ENR under different Coupon Prices.....	76
Table 4.5 LMP on buses under Different Coupon prices	76
Table 5.1 Bidding results in three cases.....	96
Table 5.2 Bidding results with Different FTR paths.....	100
Table 5.3 Generation parameter.....	102

Table 5.4 Dispatched load, LMP on buses and LSE's Revenue under different Coupon Prices with 400 MW FTR on each Path.....	103
Table 5.5 Dispatched load, LMP on buses, Optimal Coupon Price and LSE's R under different FTR Amount on each Path.....	104
Table 6.1 Parameters of Energy Storage System.....	125
Table 6.2 Generation Parameters	131
Table 6.3 Bus Parameters of LSE bidder.....	132
Table 6.4 Profit of LSE under different methods	132

LIST OF FIGURES

Figure 2.1 Reactive power capability of DFIG.....	10
Figure 2.2 PV curves before and after VAR compensation.....	13
Figure 2.3 Proposed Bi-level RPP procedure considering wind uncertainty.....	19
Figure 2.4 Flow chart of Benders decomposition procedure	22
Figure 2.5 IEEE 14-bus system integrated with two wind farms	23
Figure 2.6 Reactive power reserve with different wind power output	27
Figure 2.7 Active power output scenarios of wind farms under different correlations	28
Figure 2.8 One line diagram of IEEE 118-Bus system integrated 7 wind farms.....	30
Figure 2.9 Reactive power reserve of IEEE 118-bus system with different wind farms..	31
Figure 3.1 PJM 5-bus system with two wind farms.....	39
Figure 3.2 Bus LMP intervals from the proposed method and MC simulation.....	40
Figure 4.1 Impact of CBDR and wind power on supply and demand curves	45
Figure 4.2 Structure of the electricity market	47
Figure 4.3 Flowchart of the proposed strategic bidding	48
Figure 4.4 The illustrative figure of a LSE and its customers	49
Figure 4.5 Schematic figure of information flow for residential demand reduction modeling.....	55
Figure 4.6 Probability distribution of RPR under different coupon prices	56
Figure 4.7 Probability distribution of 24-hour RPR	56
Figure 4.8 Probability distribution of 24-hour RPR in different areas	56

Figure 4.9 Probability distribution of RPR under different coupon prices in different areas	57
Figure 4.10 The flowchart of the proposed strategic bidding model	66
Figure 4.11 PJM 5-bus system with two wind farms	67
Figure 4.12 Δ ENR versus coupon price on five typical operating points.....	68
Figure 4.13 LMP versus different load levels with various wind capacity integrated into PJM 5-bus system.....	69
Figure 4.14 Δ ENR versus coupon price with different wind power capacities	69
Figure 4.15 Impact of wind power forecast uncertainty on ENR on five typical operating points	71
Figure 4.16 LMP against load level under various wind forecast uncertainty	71
Figure 4.17 LSE bidder in IEEE 118-bus system integrated with two wind farms.....	73
Figure 4.18 LMPs of LSE's buses in IEEE 118-bus system	74
Figure 5.1 Illustration of congestion impact on the market clearing	77
Figure 5.2 Structure of the electricity market	82
Figure 5.3 Schematic of the demand reduction model and probabilistic demand reduction	86
Figure 5.4 PJM 5-bus system with two wind farms.....	96
Figure 5.5 Expected revenue under different coupon prices and different FTRs.....	97
Figure 5.6 Bus LMPs with different coupon prices.....	97
Figure 5.7 Daily load curve and optimal coupon prices, demand and expected net revenue at different hours w./o. FTR and w. FTR	99

Figure 5.8 Expected bus LMPs considering wind uncertainty and Optimal coupon price and expected net revenue under different FTR holding	103
Figure 6.1 Structure of the electricity market and LSEs with ES	109
Figure 5.2 PJM 5-bus system and generation parameters	122
Figure 5.3 Daily load curve for PJM system on Nov 23, 2014	122
Figure 6.4 LSE's profit with different energy storage capacities under different scheduling methods	124
Figure 6.5 Daily LMP at Bus D under different energy storage capacities	125
Figure 6.6 Daily energy storage status and LMP results under different methods	126
Figure 6.7 LSE bidder in IEEE 118-bus system integrated with two wind farms	128
Figure 6.8 Daily load curve for IEEE 118-bus system	129
Figure 6.9 ES status under different scheduling methods	131
Figure 6.10 Daily load curve for IEEE 118-bus system	132

LIST OF ABBREVIATIONS

RPP	Reactive Power Planning
DFIG	Doubly Fed Induction Generation
ATUS	American Time Use Survey
CURENT	Center for Ultra-Wide-Area Resilient Electric Energy Transmission
DA	Day Ahead
DMS	Distribution Management System
DOE	Department of Energy
DR	Demand Response
DRR	Demand Reduction Request
ED	Economic Dispatch
EIA	Energy Information Administration
ES	Energy Storage
EV	Electrical Vehicle
GA	Genetic Algorithm
GAMS	General Algebraic Modeling System
CBDR	Coupon based Demand Response
ISO	Independent System Operator
LMP	Locational Marginal Price
LSE	Load Serving Entity
FTR	Financial Transmission Right
MTurk	Mechanical Turk

NYISO	New York independent system operator
RECS	Residential Energy Consumption Survey
RPR	Reduced Power Ratio
UTK	University of Tennessee at Knoxville

CHAPTER 1

INTRODUCTION

1.1 General Introduction

In recent years, world-wide power systems are undergone a paradigm change with a high penetration of renewable energy resources such as wind power. The renewable energy is clean with low cost since it does not need to burn fuels. However, they are subject to significant variability and uncertainty. Therefore, integration of renewables present various challenges in power systems. Meanwhile, to offset the uncertainty from renewables, demand responses have gained considerable research interests because they can provide substantial capacity to mitigate the uncertain impact from renewables. In this dissertation, various optimization applications using bi-level optimization are investigated considering wind power and demand response.

First, reactive power planning (RPP) under this high-penetration of wind power is studied. To properly model wind generation uncertainty, a multi-scenario alternating current optimal power flow (ACOPF) framework which considers the voltage stability constraint under the worst wind scenario and transmission N-1 contingency. Recently, there are double-fed induction generator based wind generators which can provide reactive power support. Therefore, the impact of the potential reactive power support from DFIG should also be analyzed.

Then, an optimization algorithm with bounded models of wind power uncertainty is applied to calculate the intervals of Locational Marginal Prices (LMP). It is known that step changes exist in the curve of LMP under load variation, therefore, it is interesting to identify LMP intervals under wind uncertainty for market participants to assess and mitigate their risks

when price forecast is needed. Therefore an efficient and effective method to calculate the LMP intervals under wind uncertainty should be proposed without going through repetitive Monte Carlo (MC) simulation.

Next, a LSE's strategic bidding through coupon based demand response (CBDR) is modeled with bi-level optimization considering wind power uncertainty with the mathematic program with equilibrium constraints (MPEC) model. Under the smart grid initiatives, a load serving entities (LSE) may participate in the electricity market as strategic bidders by offering CBDR programs to customers. However, due to customers' versatile electricity consumption patterns under CBDR programs as well as the increasing penetration of wind generation, obtaining the deterministic bidding decision becomes unprecedented complicated for LSEs. To address this challenge, a new strategic bidding model for a LSE is proposed in which the primary objective is to maximize the LSE's profit by providing optimal CBDR considering high wind power penetration.

Further, consideration of both financial transmission right (FTR) and wind power uncertainty are considered from the perspective of LSEs. Also, a strategic scheduling model under market operation for the LSEs' ES system is studied to investigate the impact from multiple factors.

1.2 Dissertation Outline

This work will focus on applying bi-level optimization methods in power system optimization such as reactive power planning, locational marginal price evaluation, strategic bidding of load serving entities with multiple factors such as financial transmission rights and energy storages, with the consideration of wind power and demand response uncertainties.

Chapter 2 proposes reactive power planning method considering high penetration of wind power in which both new VAR devices investment cost and the system generation cost under different wind scenarios are included in the objective function and Benders decomposition is utilized to solve the two-stage optimization problem.

Chapter 3 proposes a locational marginal price interval evaluation method to analyze the impact of wind power uncertainty on LMP. The LMP interval is formulated as a bi-level optimization problem with the LMP maximization or minimization as the upper level and ISO's economic dispatch based on linear programming as the lower level.

Chapter 4 proposes a strategic bidding model for load serving entities to maximize its own profit through a coupon-based demand response program to stimulate the customers to reduce their electricity consumption. A bi-level optimization model is utilized to formulate this strategic bidding problem.

Chapter 5 proposes a strategic coupon based demand response (CBDR) bidding model considering both financial transmission right (FTR) and wind power uncertainty. A bi-level optimization model is utilized to analyze the impact of FTR.

Chapter 6 proposes a strategic energy storage (ES) scheduling problem for the LSEs' ES system. A bi-level optimization model is utilized to formulate this strategic bidding problem.

Chapter 7 concludes this work and provides suggestions for future work in applying bi-level optimization methods for power system optimization.

1.3 Contributions

The contributions of this work are listed as followed.

- This work proposes a reactive power planning method considering high penetration of wind power with wind power correlation modeled.

- This work proposes a bi-level optimization based LMP interval evaluation method. With the proposed method, LMP intervals due to the wind power uncertainty can be directly obtained instead of time-consuming Monte Carlo simulation method.
- This work proposes a strategic bidding method for load serving entities (LSEs) considering a coupon based demand response (CBDR) program in which the impact of wind power uncertainty on ISO's economic dispatch is also considered.
- This work investigates the impact from financial transmission rights on LSE's CBDR programs.
- This work proposes a bidding strategy for LSE-owned energy storages under CBDR programs.

CHAPTER 2

REACTIVE POWER PLANNING CONSIDERING HIGH PENETRATION OF WIND POWER

2.1 Introduction

The increasing penetration of wind energy presents significant challenges to the operation and planning of the bulk power transmission systems due to its intermittence and uncertainty [1]–[7]. Meanwhile, conventional synchronous-machine-based power generation, currently the main source of reactive power, is being exhausted as a result of increasing penetration of wind power and other renewables. Reactive power (VAR) is needed to accommodate the wide operation ranges of the wind generation and maintain appropriate voltage profiles because voltage collapse is often associated with reactive power deficiencies.

The goal of reactive power planning (RPP) or VAR planning is to optimize the reactive power sources in terms of locations and sizes. The problem itself is a mixed integer nonlinear programming problem which is usually challenging to the system planners. Determination of the location where VAR sources should be installed is mostly treated as an empirical problem in the real practice such that the system planner takes into account not only the system reliability needs but also the economic aspects such as generation cost. Renewable integration such as wind and solar will further complicate the optimization process by considering probabilistic scenarios. Therefore, a stochastic based multi-scenario framework is needed to better study the RPP decision of minimizing both VAR cost and generation cost under high renewable penetration.

In previous works, reactive power compensation considering wind energy presented in [8]–[11] mainly focuses on the impact of VAR compensation on the wind turbine's Low Voltage

Ride Through (LVRT) capability. The authors of those studies investigated wind turbine's dynamic VAR requirement rather than optimal sizing and placement of the system level VAR sources. In [12], voltage stability with high penetration of wind power is analyzed. In [13], a reactive power planning method regarding wind power integration for a distribution system is presented. In [14], an optimization model to determine the optimal placement of the Static VAR Compensation (SVC) devices in a power system to maximize the system load margin is proposed, in which the objective is to maximize system load margin, but neither the cost associated with VAR sources nor wind power is considered.

Voltage stability constrained optimal power flow (VSCOPF) for reactive power planning (RPP) is proposed in [15]–[25]. The dynamic security is considered in [10]. The voltage stability is included in [11, 9 20] and contingency constraints are modeled in [16, 17]. In [18], an optimization-based approach to evaluate the voltage stability margin is discussed in which the saddle-node bifurcations (SNBs) and limit-induced bifurcations (LIBs) of a power system are analyzed. In [19], a multi-period reactive power optimization method is proposed to consider the system voltage stability margin. Several methods based on nonlinear interior point algorithm or heuristic optimization algorithm such as simulated annealing are proposed in [11, 14-15]. Due to the complexity of VSCOPF, the decomposition methods to reduce the computational complexity are provided in [9, 16]. In [20], a linear/quadratic ordinary least-square multivariate regression model to statistically approximate the locus of VAR compensation with system total transfer capability is presented in order to obtain a simple model with lower computational complexity. The objectives, constraints and algorithms of RPP is reviewed in [26], which summarizes the previous RPP studies under deterministic framework. In reference [27], wind uncertainty is modeled by a large number of scenarios in the investment model. The correlation of wind speed

among several wind farms is considered for economic dispatch and system generation adequacy assessment in [28], [29] respectively. The results demonstrate that correlation is an unavoidable factor in relevant economic analysis especially when the penetration is high. References [30]–[33] show that DFIG is a viable reactive power source by studying its reactive power capability.

Note, the renewable energy such as wind power has not been considered in RPP for transmission systems in these previous studies. This is the motivation of the proposed work to address the uncertainty of wind power in RPP. In this dissertation, a multi-scenario voltage stability constrained optimal power flow (VSCOPF) model based on Benders decomposition is proposed to solve RPP problems for transmission systems with high penetration of wind energy. The uncertainty of wind power with correlation is modeled as a multi-scenario generation resource. Also, transmission contingency is considered and reactive power support from DFIG is modeled.

The rest of this dissertation is organized as follows. In Section 2, wind power model considering wind speed correlation is presented for both active and reactive power. Section 3 introduces the VSCOPF RPP model based on two sets of variables with detailed formulation. In Section 4, Benders decomposition based method is illustrated for solving the proposed model. Section 5 presents the test results from the IEEE 14-bus system and the IEEE 118-bus system. Section 6 summarizes and concludes this chapter.

2.2 Wind Power Model

Power output from a wind turbine is determined by actual wind speed. For planning studies, long term wind speeds can be modeled as a Weibull distribution which can be easily generated utilizing Monte Carlo simulation [34]–[37]. When there are multiple wind farms, their correlation should be considered.

2.2.1 Correlated Wind Power Model

To obtain correlated wind power, the correlated wind speed is needed. The Cholesky decomposition [23] is used to generate correlated Normal distribution series. It is based on obtaining the lower triangular matrix L in (2.1),

$$\Omega = LL^* \quad (2.1)$$

where Ω is the specified correlation matrix, L is the lower triangular matrix with strictly positive diagonal entries, and L^* denotes the conjugate transpose of L .

For multivariate Normal distribution, the covariance matrix is given as follows:

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \rho_{12}\sigma_1\sigma_2 \\ \rho_{21}\sigma_2\sigma_1 & \sigma_2^2 \end{bmatrix} \quad (2.2)$$

where σ_1 and σ_2 are the standard deviation in Normal distribution. In standard Normal distribution, both σ_1 and σ_2 are 1, and correlation coefficients $\rho_{12}=\rho_{21}$. Therefore, the covariance matrix Σ is identical with the correlation matrix Ω and ρ is the correlation coefficient between different wind farms [2].

The cumulative distribution function (CDF) is utilized to transform this correlated Normal distributed data to Weibull distributed data as shown in (2.3)-(2.6) [23]. F_x denotes the cumulative probability of a random variable x . For a Normal distribution, F_x is obtained from (2.3) and (2.4), and (2.5) is the CDF of Weibull distribution for wind speed in which w represents the wind speed, λ is the shape parameter and k is the scale parameter. When F_x is equal to F_w , the transformation from Normal distribution to Weibull distribution can be expressed in (2.6).

$$F_x = \frac{1}{2} \left(1 + \operatorname{erf} \left(\frac{x-u}{\sqrt{2}\sigma} \right) \right) \quad (2.3)$$

$$\text{erf}(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} dt \quad (2.4)$$

$$F_w = 1 - \exp(-(w/\lambda)^k) \quad (2.5)$$

$$w = \lambda \left[-\ln\left(1 - \frac{1}{2} \left(1 + \text{erf}\left(\frac{x}{\sqrt{2}}\right)\right)\right) \right]^{\frac{1}{k}} \quad (2.6)$$

Once the correlated Weibull distributed wind speed is generated, the correlated active power from wind turbines can be obtained through a classic wind speed-power curve. This chapter uses Vestas V90-3.0MW wind turbine model [38] to conduct the case study, which has the cut-in speed, cut-out speed, rated speed and rated wind power of 3.5 m/s, 25 m/s, 15 m/s and 3 MW respectively. In the simulation, several probabilistic scenarios are chosen for every wind farm to represent its output uncertainty.

2.2.2 DFIG Reactive Power Capability

DFIG-based wind turbine can adjust its active and reactive power independently. In other words, it has the reactive power capability at some degree. The active and reactive power D curve in Figure 2.1 can be used to approximate the DFIG's static reactive power capability. The reactive power control strategy of DFIG is either constant power factor (unity or 0.95 supplying reactive power) or operating within D curve.

2.2.3 Wind Penetration

Wind penetration can be described using three measures: energy penetration, capacity penetration, and instantaneous penetration. Energy penetration in U.S. for wind is expected to be 20% by 2030. While capacity penetration is generally used in power system planning practice. With the typical values of wind plant capacity factor (CF) and the load factor (LF), wind

capacity penetration ($P_{capacity}$) can be derived from the energy penetration (P_{energy}) in (2.7) and (2.8).

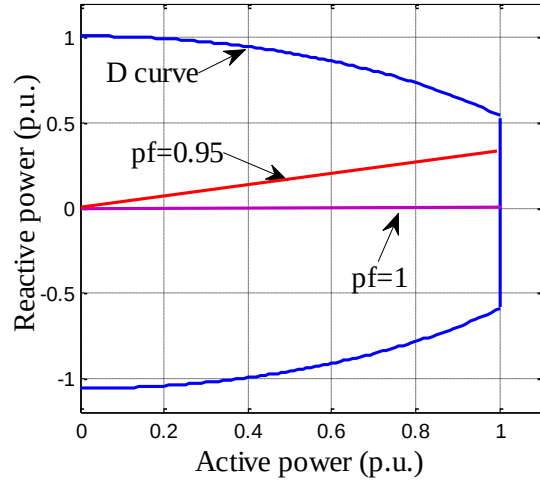


Figure 2.1 Reactive power capability of DFIG

$$P_{energy} = \frac{P_{wind} \cdot CF \cdot T}{P_{lpeak} \cdot LF \cdot T} \quad (2.7)$$

$$P_{capacity} = \frac{P_{wind}}{P_{lpeak}} = \frac{P_{energy} \cdot LF}{CF} \quad (2.8)$$

where P_{wind} is the nameplate wind power capacity; P_{lpeak} is the peak load in the system; CF is the wind capacity factor (CF is defined as the ratio between the wind energy generated over a period of time and the energy that would have been generated by constant operation at nameplate wind power capacity [39]); LF is the load factor (average load capacity/peak load capacity); and T is the duration time. The required P_{energy} is 20%, and assumed CF is 40% and LF is 60%, therefore $P_{capacity}$ is 30%. These values can be adjusted according to the actual system data.

2.3 Problem Formulation

2.3.1 Nomenclature

N	Number of VAR location candidates.
W^N	Number of wind scenarios.
N^Q	Set of reactive compensation candidate buses.
N^G	Set of generation buses.
N^L	Set of system load levels.
c_F	Fixed cost of reactive power sources (\$).
c_V	Varying cost of reactive power sources (\$/MVar).
P_{Li}, Q_{Li}	Active (reactive) power load at bus i .
$P_{Gi,s}, Q_{Gi,s}$	Active (reactive) power generation from conventional generator at bus i of scenario s on normal operating point (NOP).
$P_{Wi,s}, Q_{Wi,s}$	Active (reactive) power generation from wind generator at bus i of scenario s on NOP.
$V_{i,s}, \theta_{i,s}$	Voltage magnitude (angle) at bus i of scenario s on NOP.
$Q_{ci,s}$	Reactive power compensation at bus i of scenario s on NOP.
$P^*_{Gi,s}, Q^*_{Gi,s}$	Active (reactive) power generation at bus i of scenario s at the point of collapse (PoC).
$P^*_{Wi,s}, Q^*_{Wi,s}$	Wind active (reactive) power at bus i of scenario s on PoC.
$V^*_{i,s}, \theta^*_{i,s}$	Voltage magnitude (angle) at bus i of scenario s on PoC.
$Q^*_{c,i}$	Reactive (capacitive) power compensation at bus i on PoC.
η	System load margin.
p_s	Probability of wind and load scenario s .

μ_i Binary variable that is equal to 1 if the reactive compensation is on bus i , and 0 otherwise.

2.3.2 RPP Model

The goal of this chapter is to propose a RPP framework that is able to maintain system voltage stability margin (VSM) [40] under high penetration of wind energy while optimizing the cost. The system load margin, which is the load increment from the normal operating point (NOP) to the point of collapse (PoC), is employed as the metric to evaluate VSM shown in Figure 2.2. The objective function shown in (2.9) is to minimize the reactive power compensation cost for maintaining a required VSM as well as to minimize the generation cost under the NOP. Two sets of variables are specified corresponding to PoC and NOP for these two parts [41]–[44]. Note, [13] discusses the two sets of variables (TSV) approach for the voltage stability constrained OPF (VSCOPF) problem. In [32], a model for long-term reactive power planning is presented and [33] discusses the impact of detail generator, exponential load, and static VAR compensator models in VSCOPF on the system load ability. However, in these previous works, wind uncertainty and the reactive power support from DFIG are not discussed which is one of the key contribution of this work.

$$\min f(\mathbf{Q}_c^*, \boldsymbol{\mu}) + \sum_{d \in N^L} \frac{T_l}{T_t} \left\{ \sum_{t \in W^N} p_s \left[\sum_{i \in N^G} f(P_{Gi,s}) + \sum f(P_{Wi,s}) \right] \right\} \quad (2.9)$$

where T_l is the time that the system operates at the l^{th} load level; T_t is the total time. Further elaboration regarding the objective function is provided in the following subsections.

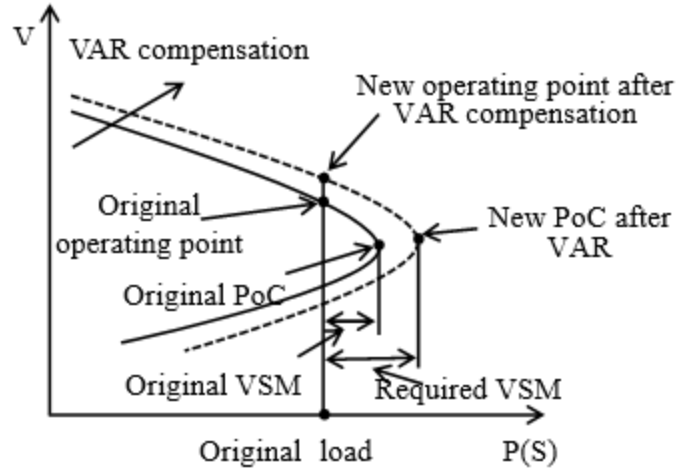


Figure 2.2 PV curves before and after VAR compensation

2.3.3 Objective Function

The first part of the objective function in (2.9) is the VAR investment cost. The constraints and the system variables for this part are applied at the operating point upon which the system load level increases with the required load margin under N-1 contingency. The objective function (2.9) is the system cost includes both VAR investment cost and generation cost. Because the generation cost is modeled as a hourly cost, so VAR investment cost should be scaled to one hour. If the lifetime of a VAR device is twenty years, the hourly investment cost (\$/h) for all VAR sources can be expressed as:

$$f(Q_c^*, \mu) = \frac{\sum_{i \in N^Q} (c_F + c_V Q_{ci}^*) \cdot \mu_i}{20 \cdot 8760} \quad (2.10)$$

The second part of (2.9) is the expected generation cost considering stochastic scenarios associated with wind power and load variation.

The fuel cost of the conventional generation is in Eq. (2.11). Also, the corresponding constraints and the system variables for the second part (the generation cost) in (2.9) are applied

for the normal operating point (NOP).

$$f(P_{Gi,s}) = K_{fp} \cdot (a_i + b_i \cdot P_{Gi,s} + c_i \cdot P_{Gi,s}^2) \quad (2.11)$$

where K_{fp} is the fuel price (\$/MBTU), a_i (MBTU), b_i (MBTU/MW) and c_i (MBTU/MW²) are the generation cost parameters.

The cost of wind power generation is mainly the operation and maintenance cost which can be expressed as follows:

$$f(P_{Wi,s}) = c^{opw} \cdot P_{Wi,s} \quad (2.12)$$

where c^{opw} is the operation and maintenance cost of wind power generator (\$/MWh).

2.3.4 Equality Constraints

The equality constraints are the nodal active and reactive power flow equations. According to the typical assumptions in voltage stability studies presented in [32], [45], [46], [47], the load margin η is a scalar value that increases uniformly with active and reactive power of all loads. Equality constraints at PoC are modeled with (2.13) and (2.14) including the load margin, and the equality constraints at NOP are modeled with (2.15) and (2.16).

$$P_{Gi,s}^* + P_{Wi,s}^* - (1+\eta) \cdot P_{Li} = V_{i,s}^* \sum_{j=1}^n V_{j,s}^* (G_{ij} \cos(\theta_{i,s}^* - \theta_{j,s}^*) + B_{ij} \sin(\theta_{i,s}^* - \theta_{j,s}^*)) \quad (2.13)$$

$$Q_{Gi,s}^* + Q_{Wi,s}^* + Q_{ci}^* - (1+\eta) \cdot Q_{Li} = V_{i,s}^* \sum_{j=1}^n V_{j,s}^* (G_{ij} \sin(\theta_{i,s}^* - \theta_{j,s}^*) - B_{ij} \cos(\theta_{i,s}^* - \theta_{j,s}^*)) \quad (2.14)$$

$$P_{Gi,s} + P_{Wi,s} - P_{Li} = V_{i,s} \sum_{j=1}^n V_{j,s} (G_{ij} \cos(\theta_{i,s} - \theta_{j,s}) + B_{ij} \sin(\theta_{i,s} - \theta_{j,s})) \quad (2.15)$$

$$Q_{Gi,s} + Q_{Wi,s} + Q_{ci,s} - Q_{Li} = V_{i,s} \sum_{j=1}^n V_{j,s} (G_{ij} \sin(\theta_{i,s} - \theta_{j,s}) - B_{ij} \cos(\theta_{i,s} - \theta_{j,s})) \quad (2.16)$$

2.3.5 Inequality Constraints

The inequality constraints are the physical and security limits similar to those presented in [13], [48]. The formulations of the two sets of inequality constraints for PoC and NOP are very similar, as shown in [13]. The constraints such as the active and reactive power output limits of conventional generation (2.17) and (2.18), bus voltage magnitude and angle limits (2.19) and (2.20) in which the reference bus voltage magnitude and angle are fixed at the given value, transmission line apparent power limits (2.21) are the same with that in [14] and should be applied to both PoC and NOP. The generators' voltage and reactive power limits are different with that in [18, 19] because N-1 contingency are considered in our RPP model which is not included in the VAR operation model in [18, 19]. At PoC, the reactive compensation capability limits are in (2.22). The number of total candidate VAR installation buses is (2.23). At NOP, the reactive power limit of VAR sources is shown in (2.24). The active power limit of wind power is in (2.25) for NOP, and $P_{Wi,s}^{\max}$ is the maximum power output of wind farm i in the s^{th} scenario. In (2.26) and (2.27), DFIG has different reactive power limits for different reactive power control strategies.

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max} \quad (2.17)$$

$$Q_{Gi}^{\min} \leq Q_{Gi} \leq Q_{Gi}^{\max} \quad (2.18)$$

$$V_i^{\min} \leq V_i \leq V_i^{\max} \quad (2.19)$$

$$-\pi \leq \theta_i \leq \pi \quad (2.20)$$

$$-S_{ij}^{\max} \leq S_{ij} \leq S_{ij}^{\max} \quad (2.21)$$

$$\mu_i Q_{Ci}^{\min} \leq Q_{Ci}^* \leq \mu_i Q_{Ci}^{\max} \quad (2.22)$$

$$\sum_i^n \mu_i \leq N \quad (2.23)$$

$$Q_{ci,s}^{\min} \leq Q_{ci,s} \leq Q_{ci,s}^{\max} \quad (2.24)$$

$$0 \leq P_{Wi,s} \leq P_{Wi,s}^{\max} \quad (2.25)$$

$$Q_{Wi,s}^{*\min}(P_{Wi,s}^*) \leq Q_{Wi,s}^* \leq Q_{Wi,s}^{*\max}(P_{Wi,s}^*) \quad (2.26)$$

$$Q_{Wi,s}^{\min}(P_{Wi,s}) \leq Q_{Wi,s} \leq Q_{Wi,s}^{\max}(P_{Wi,s}) \quad (2.27)$$

2.4 Problem Decomposition

The VAR planning problem in this chapter is modeled as voltage stability constrained OPF (VSCOPF). The major challenge for the VSCOPF is the requirement of two sets of variables and constraints corresponding to the NOP and PoC. To address this challenge, the optimization model is decomposed into two levels such that at each level only one set of variables and constraints are applied. The upper-level (Master problem) is VAR allocation optimization under PoC. The lower-level (Sub-problem) is the traditional ACOPF with given VAR allocation information from the upper-level solution, minimizing expected generation cost considering all scenarios under NOP. Benders decomposition is utilized to solve this bi-level optimization problem [9].

2.4.1 Sub-problem

The sub-problem solves ACOPF for all scenarios and the optimization model for one scenario in the v^{th} iteration is given by (2.28)-(2.30):

$$\mathbf{min} \quad z_{sub,s} = f(P_{Gi,s} | \mathbf{Q}_c^{*(v)}, \mathbf{x}_s) \quad (2.28)$$

$$\text{s.t. } g_s(\mathbf{Q}_c^{*(v)}, \mathbf{x}_s) \leq 0 \quad (2.29)$$

$$\mathbf{Q}_{c,s} \leq \mathbf{Q}_c^{*(v)} : \omega_s^{(v)} \quad (2.30)$$

where s represents the index of a probabilistic scenario with certain wind power output and load; $z_{sub,s}$ is the generation cost in scenario s ; $\mathbf{x}_s$ are the operation variables; $\mathbf{Q}_c^{*(v)}$ is the VAR allocation result obtained from the master problem in iteration v ; $\mathbf{Q}_{c,s}$ is the reactive power output of VAR sources in scenario s . The constraint in (2.29) contains active and reactive power flow equation corresponding to (2.15) and (2.16) in section 3 and also the inequality constraints mentioned in the previous section as well. The variable $\mathbf{Q}_c^{*(v)}$ has the same value in all scenarios. $\omega_s^{(v)}$ is the dual variable associated with inequality constraint in (2.30).

The number of scenarios in sub-problem increases exponentially with the number of wind farms. The computational effort for solving the scenario-based optimization model depends highly on the number of scenarios. Therefore, it is necessary to obtain a subset of scenarios that can best capture the impact from the original set with reasonable runtime. The scenario reduction approach employed in this chapter is described in details in [49].

2.4.2 Master Problem

Master problem at the v^{th} iteration can be formulated as:

$$\min \quad z_m = f(\mathbf{Q}_c^*, \boldsymbol{\mu}) + \alpha \quad (2.31)$$

$$\text{s.t. } g(\mathbf{Q}_c^*, \mathbf{x}^*) \leq 0 \quad (2.32)$$

$$\alpha \geq \sum_{t \in W^N} p_s z_{sub,s}^{(m)} + \sum_{t \in W^N} \sum_{i \in N^Q} p_s \omega_{i,s}^{(m)} (Q_{ci}^* - Q_{ci}^{*(m)}) \quad (2.33)$$

$$m = 1, 2, \dots, v-1$$

$$z_m \leq z^{opt} \quad (2.34)$$

where v, m are index of the iteration of Benders algorithm; α, ω are auxiliary variable in Benders algorithm. Also, the constraint in (2.32) contains active and reactive power flow equation equivalent to (2.13) and (2.14), and the inequality constraints mentioned in previous section. The

inequality constraint in (2.34) is to guarantee that the objective is lower or equal to the current solution. p_s is the probability of the s^{th} wind power output and load scenario.

Since voltage collapse is often associated with the reactive power deficiency [50], it is the first priority to identify the worst wind scenario in which the system has the least reactive power reserve. Here, the worst wind scenario is typically obtained by checking the voltages through power flow analysis.

Then the system N-1 contingencies are modeled in this RPP study. The changes with one transmission line outage [51], [52] in $\mathbf{Y}_{bus}$ is shown in (2.35) and (2.36). A new $\mathbf{Y}_{bus}$ matrix is calculated for the transmission line outage contingency. The outage of one line is determined by β_l , if $\beta_l=0$ there is no line outage ($\mathbf{Y}_{bus}^0$); otherwise, if $\beta_l=1$, a contingency with line l outage occurs ($\mathbf{Y}_{bus}^l$),

$$\mathbf{Y}_{bus} = \mathbf{Y}_{bus}^0 - \mathbf{Y}_{bus}^l \quad (2.35)$$

$$\mathbf{Y}_{bus}^l = \begin{bmatrix} \beta_l y_{ij0} & -\beta_l y_{ij} \\ -\beta_l y_{ji} & \beta_l y_{ji0} \end{bmatrix} \quad (2.36)$$

where y_{ij0} , y_{ij} , y_{ji} , y_{ji0} are the branch admittances.

Therefore, the master problem optimizes VAR allocation under the worst contingency and wind power output scenario to maintain the required VSM. Typically, the worst contingency can be obtained through the N-1 contingency ranking method [53]. The proposed RPP procedure is illustrated in Figure 2.3. The left part is the wind scenario creation and N-1 contingency ranking process to obtain the worst case; while the right part is the Benders decomposition procedure. The detail procedure for the Benders decomposition is discussed in the next subsection.

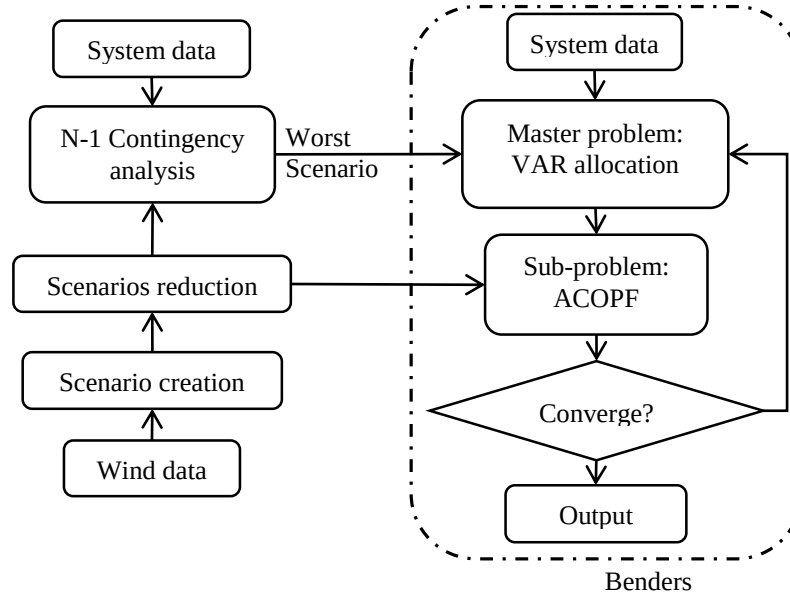


Figure 2.3 Proposed Bi-level RPP procedure considering wind uncertainty

2.4.3 Benders Decomposition Procedure

The proposed Benders decomposition procedure for the master problem and subproblem can be stated as:

- 1) *Get Initial Solution.* Set $\alpha = 0$ and $z^{opt} = \infty$, where z^{opt} is the global optimum value. Solve the master problem and obtain the initial $Q_{ci}^{*(0)}$, $\mu_i^{(0)}$, and $z_{varcost}^{(0)} = f(Q_c^{*(0)}, \mu^{(0)})$
- 2) *Benders Initialization.* Set the Benders iteration counter. $v=1$, $Q_{ci}^{*(v)} = Q_{ci}^{*(0)}$, $\mu_i^{(v)} = \mu_i^{(0)}$, and $z_{down}^{(v)} = -\infty$. $z_{down}^{(v)}$ and $z_{up}^{(v)}$ are the lower and upper bound of the objective function in the v^{th} Benders iteration.
- 3) *Sub-problem Solutions.* Solve the sub-problem (28)-(30) for every wind and load scenario. After solving all scenarios, update the upper bound of the objective function.

$$z_{up}^{(v)} = z_{varcost}^{(v-1)} + \sum p_s \cdot z_{sub,s}^{(v)}$$

The solution to the sub-problem provides the objective values $z_{sub,s}^{(v)}$ and the dual variable $\omega_s^{(v)}$.

- 4) *Global Solution Update.* If $z_{up}^{(v)} < z^{opt}$, update the global solution $z^{opt} = z_{up}^{(v)}$, $Q_c^{opt} = Q_c^{*(v+1)}$, $\mu^{opt} = \mu^{(v)}$.
- 5) *Convergence Check.* If $|z_{up}^{(v)} - z_{down}^{(v)}| \leq \varepsilon |z_{down}^{(v)}|$, then a solution with the confidence level ε has been found and output the result; otherwise, it continues below.
- 6) *Master Problem Solution.* Update Benders iteration counter $v = v + 1$, solve the master problem (31)-(34) with the parameters $(z_{sub,s}^{(v)}, \omega_s^{(v)})$ from step 3) and obtain $Q_c^{*(v+1)}$, $\mu^{(v+1)}$. Update the lower bound of the objective $z_{down}^{(v+1)} = z_m^{(v+1)}$, $z_{varcost}^{(v+1)} = f(Q_c^{*(v+1)}, \mu^{(v+1)})$. The algorithm continues in 3.

The complete program flow chart is presented in Figure 2.4 to better illustrate the proposed approach.

2.5 Case study and results

The proposed multi-scenario VSCOPF based RPP model is tested on a modified IEEE 14-bus system and IEEE 118-bus system. Simulation is performed using General Algebraic Modeling System (GAMS) on a computer with dual-core Core-i5 2.6-GHz CPU, 4 GB RAM, and Window 7 with Bonmin as the MINLP solver and SNOPT as the NLP solver [54]. The test cases simulation model and obtained results are elaborated in the following subsections.

2.5.1 IEEE 14-bus System Model

IEEE 14-bus system integrated with two wind farms used in the simulation model is shown in Figure 2.5. The detailed system parameters can be found in [55] and generation cost data is given in Table 2.1. The reactive power capacity of existing generators is reduced to half to create a stressed system that is vulnerable to voltage collapse. The modified system data are

utilized as the “heavy-load” case. The “medium-load” and “light-load” cases are obtained by scaling all loads down by 0.8 and 0.64 [14]. The heavy-load and light-load cases are assumed to be 1000 h each, and hence, the medium-load case is 6760 h in a total of 8760 h (one year). To consider the negative correlation between wind power and load peak, the maximum wind power output for “light-load”, “medium-load” and “heavy-load” are 100%, 95% and 90% of the installation capacity of wind farms. For the voltage stability concern, the system load margin η is set at 5% for the heavy-load case under N-1 contingencies. The worst N-1 contingency of the high voltage transmission line outage is the line outage of Bus 2 to Bus 4. The operation cost of wind power generator c^{opw} is taken as \$3/MWh based on [56], which can be adjusted according to the actual system condition. The hourly fixed cost and varying cost of VAR sources are 30 \$/h and 1.5 \$/(MVar·h), respectively. The VAR candidate buses are all the load buses {4, 5, 7, 9, 10, 11, 12, 14} since this is a small system. Note, for a large system such as the IEEE 118-bus system shown next, VAR candidate buses can be selected based on voltage stability requirement.

Two wind farms with capacity of 47MW and 30MW are connected at Bus 2 and Bus 13 in which all the wind turbines are DFIG. With the total load being 257MW, the wind capacity penetration is 30%. In this case, 11 scenarios (from 0% to 100% capacity with 10% increment) are chosen for every wind farm to represent its output uncertainty. Three different types of DFIG VAR control scheme are modeled in the following cases:

Case a: unity power factor;

Case b: power factor being 0.95 (supplying VAR);

Case c: operating in D curve.

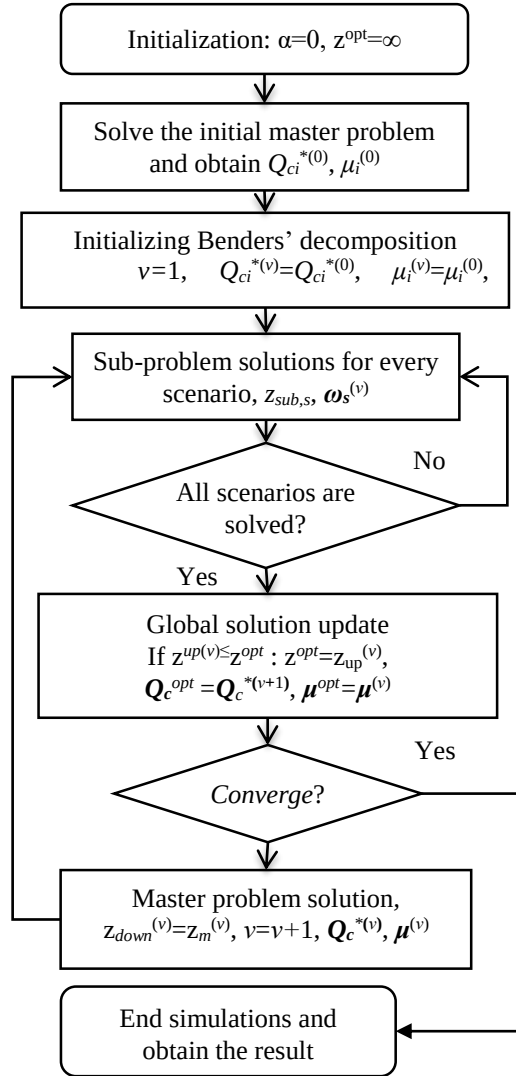


Figure 2.4 Flow chart of Benders decomposition procedure

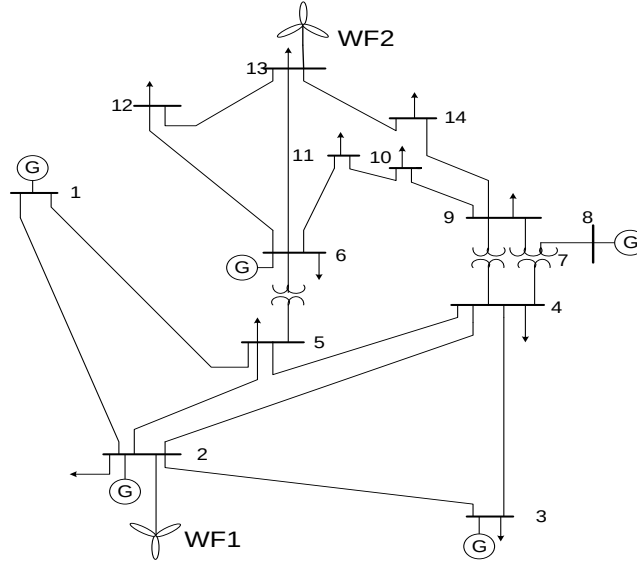


Figure 2.5 IEEE 14-bus system integrated with two wind farms

In [57], the analysis of wind speed data in Sweden shows a strong correlation between adjacent wind farms. The shape parameter λ and scale parameter k of Weibull distribution are set as 8.13, 1.99 and 8.24, 2.3, respectively.

The proposed RPP method is applied to the modified IEEE 14-bus system under different correlations between wind farms and different reactive power control strategies for DFIG. The system reactive power reserves under different cases were analyzed to obtain the worst case scenarios in which the system has the lowest reactive power reserve. Different optimization objectives are also applied to compare the VAR requirements and associated costs for each of the scenarios.

Figure 2.6 illustrates the system reactive power reserve with different wind farms' power output for different reactive power control strategies of DFIG. The results are obtained from power flow analysis by relaxing the reactive power limits of generators. The negative reactive power reserve means that the generators' reactive power output exceed their original limits such

that the system lacks reactive power. In this figure, the reactive power reserve is the lowest at 0 MW for both wind farms in Case a and Case b. In Case c, the corresponding scenario is 47 MW and 30MW for WF1 and WF2, respectively.

Table 2.1 Unit Parameter of IEEE 14 Bus System

Unit No.	Bus No.	Unit Cost Coefficients			Fuel Price(\$/MBtu)	Pmax (MW)
		a(MBtu/u)	b(MBtu/u/MW)	c(MBtu/MW ²)		
1	1	0	10	0.01	2.25	200
2	2	5	35	0.02	2.25	100
3	3	0	40	0.03	2.25	100
4	6	5	40	0.03	2.25	100
5	8	5	40	0.03	2.25	100

Figure 2.7 shows the active wind power output scenarios under different correlations. Therefore, mapping the scenarios in Figure 7 into the system reactive power reserve figure in Figure 2.6, the worst wind scenario of different correlations can be obtained. The worst scenarios of three cases are listed in Table 2.2. Table 2.3 presents VAR allocation results with the objective of minimizing the VAR cost. In Table 4, optimization results with the minimization objective being the total cost including VAR cost and generation cost is presented.

Since the worst scenarios are same for Case a and Case b under different correlations as shown in Table 2.2, the VAR allocation results are also the same for Case a and Case b as shown in Table 2.3. In Case c, the worst scenario is 47MW and 30MW for WF1 and WF2 respectively when the correlation coefficient is in the range 0 to 1.0. While with a negative correlation of -1.0 and -0.5, the worst scenario changes to 0 MW and 30 MW for WF1 and WF2 respectively. The reactive power shortage under the negative correlation (i.e., correlation = -0.5 and -1.0) is less than that under the nonnegative correlation (i.e., correlation = 0, 0.5 and 1.0) as can be determined from Figure 2.6. It can be concluded that, with the objective of VAR cost

minimization, if different correlations lead to the different worst scenarios, then correlation will change the optimized VAR allocation results.

When generation cost is included in the objective, VAR allocation result changes among different correlations as can be seen from Table 2.4. The difference between the results presented in Tables 2.3 and Table 2.4 demonstrate that the optimization objective is a major factor for VAR planning. Although VAR cost increases when reactive power support is desired, the generation cost reduction can compensate this investment increment.

In Table 2.4, it also shows that the total cost increases with the correlation while this pattern is not obvious for the VAR cost. It also can be concluded that VAR support from wind farms reduce the total cost regardless of the correlation, especially for Case c. For the VAR cost, the benefit of VAR support is evident only when DFIG operates in D curve.

The number of iterations, CPU computational time and number of wind scenarios under different correlations are listed in Table 2.5. Computational time varies from about 0.5 to 12 minutes, all within acceptable range for a planning study of moderate size and complexity. The CPU time varies linearly with the number of wind scenarios. Therefore, in the RPP of a power system integrated with multiple wind farms, the scenario reduction technique should be implemented to obtain a reasonable subset of wind scenarios to acquire both the results accuracy and the computational efficiency.

Table 2.2 The Worst Wind Scenarios under Different Cases

	ρ	WF1	WF2
Case a	-1~1	0	0
Case b	-1~1	0	0
Case c	-1~-0.5	0	30
	0~1	47	30

Table 2.3 VAR Allocation considering the VAR Cost

	ρ	VAR size (Bus)	Fuel cost (\$/h)	VAR cost (\$/h)	Total cost (\$/h)
Case a	-1	22.6(9)	7896.1	63.9	7960.0
	-0.5	22.6(9)	7898.4	63.9	7962.3
	0	22.6(9)	7903.9	63.9	7967.8
	0.5	22.6(9)	7911.6	63.9	7975.5
	1	22.6(9)	7923.4	63.9	7987.3
Case b	-1	21.1(14)	7909.8	61.6	7971.5
	-0.5	21.1(14)	7912.5	61.6	7974.1
	0	21.1(14)	7918.5	61.6	7980.1
	0.5	21.1(14)	7927.1	61.6	7988.7
	1	21.1(14)	7928.3	61.6	7989.9
Case c	-1	15.2(14)	7901.4	52.8	7954.2
	-0.5	15.2(14)	7904.1	52.8	7956.9
	0	18.7(14)	7909.6	58.1	7967.7
	0.5	18.7(14)	7918.3	58.1	7976.4
	1	18.7(14)	7930.1	58.1	7988.2

Table 2.4 VAR Allocation Considering the Total Cost

	ρ	VAR size (Bus)	Fuel cost (\$/h)	VAR cost (\$/h)	Total cost (\$/h)
Case a	-1	34.6(9)	7874.1	82.0	7956.1
	-0.5	30.7(9)	7882.8	76.0	7958.8
	0	30.9(9)	7888.5	76.3	7964.8
	0.5	31.0(9)	7896.2	76.6	7972.8
	1	29.8(9)	7908.8	74.7	7983.5
Case b	-1	35.2(9)	7870.4	82.7	7953.1
	-0.5	33.0(9)	7876.3	79.6	7955.8
	0	32.0(9)	7883.7	78.0	7961.7
	0.5	29.9(9)	7894.8	74.9	7969.6
	1	28.9(9)	7907.0	73.3	7980.3
Case c	-1	25.5(9)	7868.4	68.3	7936.7
	-0.5	25.5(9)	7872.1	68.2	7940.3
	0	25.6(9)	7878.7	68.4	7947.1
	0.5	25.7(9)	7887.5	68.6	7956.1
	1	23.8(9)	7902.3	65.7	7968.0

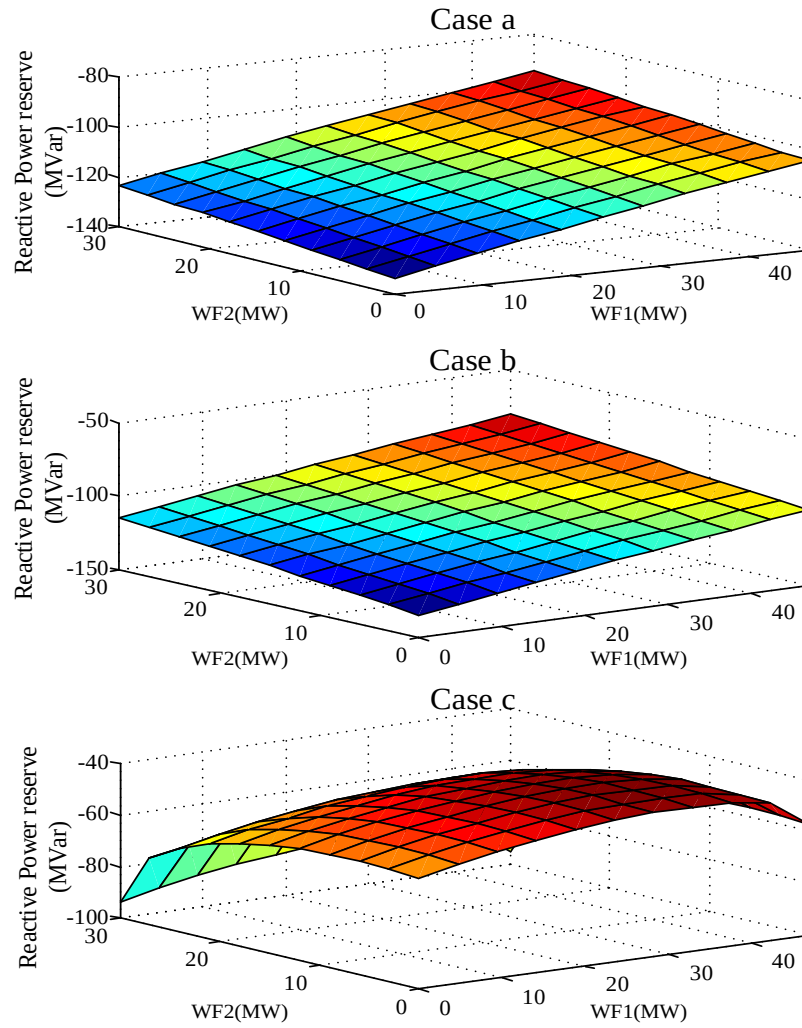


Figure 2.6 Reactive power reserve with different wind power output

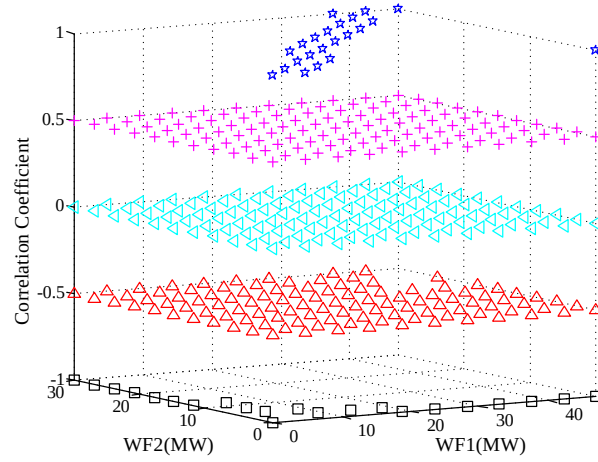


Figure 2.7 Active power output scenarios of wind farms under different correlations

Table 2.5 No. of Iterations, CPU time and Wind Scenarios of Different Cases

	ρ	Iterations	CPU(s)	Wind scenarios
Case a	-1	8	102	22
	-0.5	7	327	113
	0	8	448	121
	0.5	8	408	121
	1	8	153	22
Case b	-1	8	76	22
	-0.5	8	398	113
	0	8	402	121
	0.5	8	383	121
	1	9	189	22
Case c	-1	7	85	22
	-0.5	7	321	113
	0	6	301	121
	0.5	7	367	121
	1	7	68	22

2.5.2 IEEE 118-Bus System

The IEEE 118-bus system model integrated with 7 wind farms is used for the second case study here. The system has a total wind power installation capacity of 1280MW and a system load of 4242MW, such that the wind power capacity penetration is still 30%. The detail system parameters can be obtained from [58] and the generation data is shown in Table 2.7. In order to stress the system, reactive power capacity of the existing generators is reduced by half and some generators are removed as well. The load uncertainty model is the same with the IEEE 14-bus system case study. The system load margin for the concern of voltage stability is 5% for the heavy-load case under N-1 transmission contingencies. The worst N-1 contingency is the outage of transmission line connecting Bus 26 to Bus 30 [38]. The VAR installation candidate buses are {15, 29, 39, 41, 75, 107, 113, 118} which are obtained from the feasibility analysis [59].

Table 2.6 Wind Farms Data

Group	Bus	Wind rated power (MW)	λ	k
1	2, 5, 12	210, 170, 165	8.11	1.79
2	44, 53	200, 155	7.24	2.12
3	82, 86	185, 195	7.36	2.03

The pertinent data for the wind generations are given in Table 2.6. Seven wind farms are divided into 3 groups based on their locations. Correlation among three groups of wind farms can be expressed using the correlation matrix shown in (37). For each wind farm, there are 11 power output scenarios from 0 to 100% with 10% power increment. A total of 918 wind power scenarios with 50000 wind speed samples for each wind farm are generated considering their correlations. Scenario reduction has been applied to decrease the scenario number in order to

reduce the total simulation time. The results under different scenario numbers for Case a (unity power factor), Case b (0.95 power factor), and Case c (D curve operating) were studied.

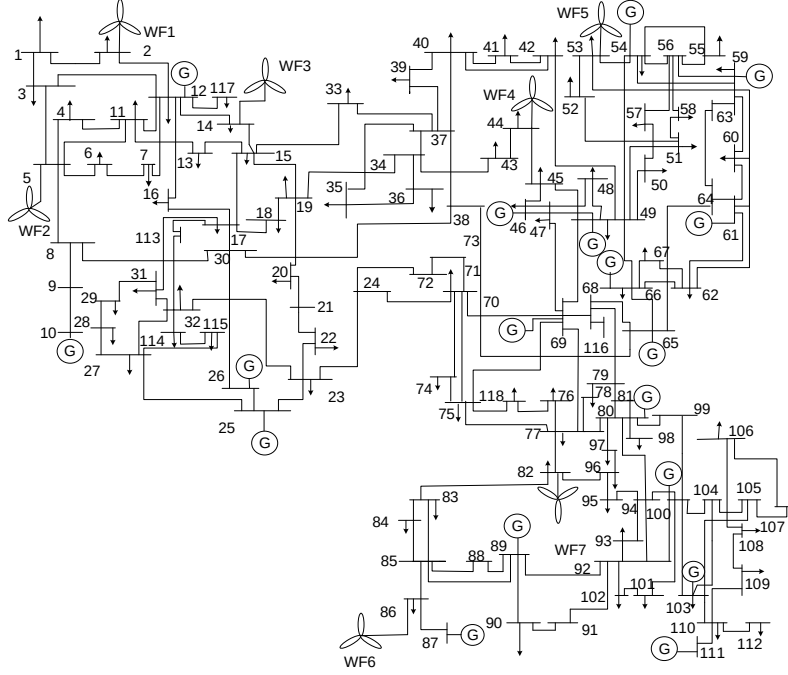


Figure 2.8 One line diagram of IEEE 118-Bus system integrated 7 wind farms

$$\begin{bmatrix} 1 & 0.86 & 0.75 \\ 0.86 & 1 & 0.79 \\ 0.75 & 0.79 & 1 \end{bmatrix} \quad (37)$$

G1 G2 G3

The system reactive power reserve curves with each wind farm integrated to the system separately under different cases (Case a, Case b and Case c) are presented in Figure 2.9(a), (b) and (c). From Figure 2.9, the worst scenarios chosen for the master problem are listed in Table 2.8. The VAR allocation results are listed in Table 2.9, Table 2.10 and Table 2.11.

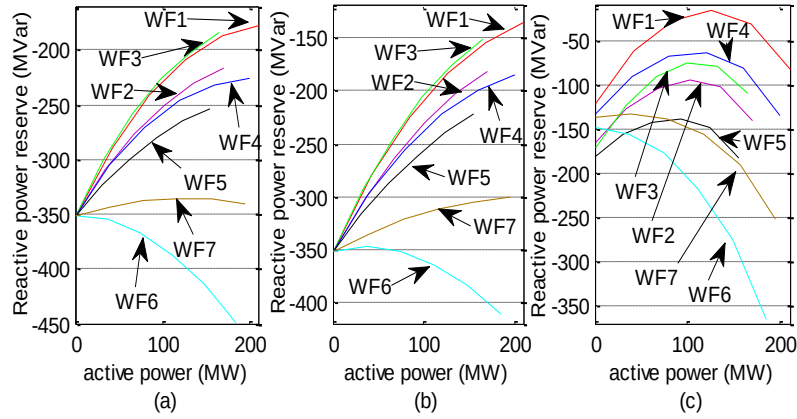


Figure 2.9 Reactive power reserve of IEEE 118-bus system with different wind farms

Table 2.7 Unit Parameter of IEEE 118 Bus System

Unit No.	Bus No.	Unit Cost Coefficients			Fuel Price(\$/ MBtu)	Pmax (MW)
		a(MBtu)	b(MBtu/ MW)	c(MBtu/ MW ²)		
1	10	6.78	12.8875	0.010875	2.25	700
2	12	6.78	12.8875	0.010875	2.25	600
3	25	6.78	12.8875	0.010875	2.25	500
4	26	32.96	10.7600	0.003000	2.25	650
5	46	10.15	17.8200	0.012800	2.25	200
6	49	28	12.3299	0.002401	2.25	350
7	54	28	12.3299	0.002401	2.25	300
8	59	39	13.2900	0.004400	2.25	300
9	61	39	13.2900	0.004400	2.25	300
10	65	64.16	8.3391	0.010590	2.25	500
11	66	64.16	8.3391	0.010590	2.25	400
12	69	6.78	12.8875	0.010875	2.25	500
13	80	6.78	12.8875	0.010875	2.25	700
14	87	32.96	10.7600	0.003000	2.25	300
15	89	6.78	12.8875	0.010875	2.25	700
16	100	6.78	12.8875	0.010875	2.25	500
17	103	17.95	37.6968	0.028302	2.25	640
18	111	10.15	17.8200	0.012800	2.25	700

Table 2.8 Scenarios for Master Problem

	Wind farm power output (MW)						
	1	2	3	4	5	6	7
Case a, b	0	0	0	0	0	0	0
Case c	210	170	165	200	155	185	195

Table 2.9 Impact of Scenario Reduction in Case a

Scen. Num.	700	800	918
Objectives: VAR cost			
Fuel cost	127606.2	129693.4	133237.1
VAR cost	105.9	105.9	105.9
Total cost	127712.1	129799.3	133343.0
VAR Size (Bus)	29.8(39), 0.8(107)	29.8(39), 0.8(107)	29.8(39), 0.8(107)
Objectives: Total cost			
Fuel cost	126206.6	128774.9	132313.1
VAR cost	1080	540	540
Total cos	127286.6	129314.9	132853.1
VAR Size (Bus)	100(15, 29, 75, 107, 113, 118)	100(15), 100(113), 100(118)	100(15), 100(113), 100(118)
CPU (s)	6874	10414	14211

Similar to the results in Table 2.3 and Table 2.4, results from Table 2.9, Table 2.10 and Table 2.11 indicate that the optimal VAR allocation is influenced by the optimization objective and the reactive power support from DFIG. Changing the objective from VAR cost to total cost will increase the installed VAR capacity and the corresponding VAR cost, but the benefit from generation cost reduction can counteract this investment increment. Also VAR support from DFIG allows significant reduction in the capacity of new VAR sources, such that the VAR cost is reduced sharply with more reactive power from DFIG.

The RPP results of these three cases under different scenario numbers are also presented in Table 2.9 to Table 2.11. It demonstrates that in RPP study, integration of the original wind power scenario sets is pivotal for the optimization results. The VAR allocations change when the scenario number decreases. But with DFIG providing more reactive power support, the same VAR allocation can be maintained with less number of wind scenarios. For example, in Table 2.9, results change when the scenario number is reduced to 700. While in Table 2.10 and Table 2.11, this change happens when the scenario number reduces to 40 and to 400, respectively.

Table 2.10 Impact of Scenario Reduction in Case b

Scen. Num.	40	50	918
Objectives: VAR cost			
Fuel cost	121818.4	120125.7	133459.0
VAR cost	105.9	105.9	105.9
Total cost	121924.3	120231.6	133564.9
VAR Size (Bus)	29.8(39), 0.8(107)	29.8(39), 0.8(107)	29.8(39), 0.8(107)
Objectives: Total cost			
Fuel cost	121265.1	119712.3	133022.0
VAR cost	376.8	243.0	243.0
Total cos	121641.9	119955.3	133265.0
VAR Size (Bus)	56.9(15), 77.2(75), 57.1(118)	22.0(41), 100(118)	22.0(41), 100(118)
CPU (s)	636	732	8675

Table 2.11 Impact of Scenario Reduction in Case c

Scen. Num.	400	500	918
Objectives: VAR cost			
Fuel cost	124023.7	125104.7	132683.7
VAR cost	34.3	34.3	34.3
Total cost	124058.0	125139.0	132718.0
VAR Size (Bus)	2.9(41)	2.9(41)	2.9(41)
Objectives: Total cost			
Fuel cost	124003.2	125104.7	132683.7
VAR cost	54.7	34.3	34.3
Total cos	124057.9	125139.0	132718.0
VAR Size (Bus)	16.5(41)	2.9(41)	2.9(41)
CPU (s)	3199	4411	8012

2.6 Conclusions

In this chapter, a voltage stability constrained reactive power planning model considering high penetration of wind energy is proposed. The main contributions are summarized below.

1. Reactive Power Planning (RPP) model considering high penetration of wind generation in the transmission system is proposed based on a stochastic multi-scenario VSCOPF framework to consider wind uncertainty. Correlations among different wind plants as well as transmission N-1 contingency are modeled in the study.
2. Traditional RPP problem has been re-defined as a two stage optimization process that includes both the VAR compensation cost and the expected generation cost considering the impact of wind uncertainty. Benders' decomposition is applied to solve the stochastic two stage problem.
3. Simulation results suggests that total cost is a better optimization objective as compared to only VAR cost in RPP with wind power integrated in power systems and correlation among wind farms impacts both VAR costs and generation costs, hence it is an important factor in RPP considering high penetration of wind power.
4. Scenario reduction can change the VAR allocation results. When DFIG provides more reactive power, same allocations can be maintained under a less number of scenarios shown in Case b and Case c.
5. DFIG's reactive power capability lends itself as an alternative resource to effectively facilitate the wind power incorporated RPP process with the proposed method.

Future work is needed to address the cost of DFIG reactive power support which is mainly the operation and maintenance cost. The system planners and operators need to optimize the system operation condition considering the reactive power support from DFIG.

CHAPTER 3

EVALUATION OF LOCATIONAL MARGINAL PRICE INTERVALS CONSIDERING WIND POWER UNCERTAINTY

3.1 Introduction

The locational marginal pricing (LMP) methodology is widely utilized in power markets to calculate the electricity prices and to evaluate the transmission congestion cost [3], [60]. Step change characteristics of LMP under system load variation has been identified and discussed in [45]. The critical load level (CLL) observed in the previous work [1] [45] has proven to be the measure of identifying the price ranges where LMPs stay invariable under system load variation. The concept of CLL is also employed in [61] for load frequency control. Based on similar motivation, it is interesting to investigate the impact on LMP because of variable wind power, which brings additional sources of variation to affect system's actual operating point. As a result, this could lead to LMP variations. Therefore, it is desired to find a solution to efficiently obtain the LMP intervals under the variation of wind power output. This chapter develops a bi-level optimization model to tackle the wind power variation in the market clearing process, which is essentially a linear programming (LP) problem given by:

$$\min \sum_{i=1}^N (c_i \times G_i + c_{wi} \times P_{wi}) \quad (3.1a)$$

$$\text{s.t. } \sum_{i=1}^N (G_i + P_{wi}) = \sum_{i=1}^N D_i : \lambda \quad (3.1b)$$

$$-L_l \leq \sum_{i=1 \sim N} GSF \times (G_i + P_{wi} - D_i) \leq L_l : \mu_l^{\min}, \mu_l^{\max}, \forall l = 1 \sim M \quad (3.1c)$$

$$G_i^{\min} \leq G_i \leq G_i^{\max} : \omega_i^{\min}, \omega_i^{\max}, \forall i = 1 \sim N \quad (3.1d)$$

$$0 \leq P_{wi} \leq P_{wi}^{\max} : \phi_i^{\min}, \phi_i^{\max}, \forall i = 1 \sim N \quad (3.1e)$$

where N is the number of buses; M is the number of lines; c_i and c_{wi} are bidding price for conventional generation and wind power, respectively, at bus i (\$/MWh); G_i is the conventional generation output; GSF is the generation shift factor matrix; $G_i^{\max}$ and $G_i^{\min}$ are the maximum and minimum generation output at bus i ; $P_{wi}^{\max}$ is the maximum available wind power output; D is the demand at bus i (MWh); and the variables on the right side of the colon are the dual variables associated with the equality and inequality constraints on the left.

The locational marginal price (LMP) π_i can be calculated from the Lagrangian function of the above ED problem. This function and LMP can be written as:

$$\begin{aligned} \psi = & \left(\sum_{i=1}^N c_i \times G_i + c_{wi} \times P_{wi} \right) - \lambda \left(\sum_{i=1}^N G_i + P_{wi} - \sum_{i=1}^N D_i \right) \\ & - \sum_{l=1}^M \mu_l^{\min} \left(\sum_{i=1}^N GSF_{l-i} \times (G_i + P_{wi} - D_i) + L_l \right) \\ & - \sum_{l=1}^M \mu_l^{\max} \left(L_l - \sum_{i=1}^N GSF_{l-i} \times (G_i + P_{wi} - D_i) \right) \\ & - \sum_{i=1}^N \omega_i^{\min} (G_i - G_i^{\min}) - \sum_{i=1}^N \omega_i^{\max} (G_i^{\max} - G_i) \\ & - \sum_{i=1}^N \phi_i^{\min} P_{wi} - \sum_{i=1}^N \phi_i^{\max} (P_{wi}^{\max} - P_{wi}) \end{aligned} \quad (3.1f)$$

$$\pi_i = \frac{\partial \psi}{\partial D_i} = \lambda + \sum_{l=1}^M GSF_{l-i} (\mu_l^{\min} - \mu_l^{\max}) \quad (3.1g)$$

3.2 LMP Interval and its Bi-level Optimization Form

In view of the challenges raised by the time consuming Monte Carlo approach to evaluate the CLLs, it can be replaced by the bi-level optimization model proposed below to achieve the same level of accuracy in predicting the intervals with much faster processing time. Taking LMP calculation for bus i as an example, the problem is formulated as below:

$$\text{Upper Level: } \max \pi_i \text{ (or } \min \pi_i) \quad (3.2a)$$

$$\text{s.t. Lower Level: ED optimization problem } \{(3.1a)-(3.1e)\} \quad (3.2b)$$

$$\underline{P_{wf,i}} \leq P_{wi}^{\max} \leq \overline{P_{wf,i}} \quad (3.2c)$$

where $\underline{P_{wf,i}}, \overline{P_{wf,i}}$ is the forecast lower and upper bound of the maximum wind power output. In other words, the maximum wind output is modeled as a bounded interval constraint in the upper level. The objective (3.2a) is the LMP formulation in (3.1g).

In the above formulation, (3.2a) is to find the maximum LMP (or minimum LMP) at a particular bus under wind uncertainty modeled in (3.2c). Again, the motivation here is for a market player to assess the LMP uncertainty due to wind power variation. Note, it is not necessarily true that the highest wind output will correspond to the lowest LMP at that particular bus. Also, (3.2a) should be done to find the maximum LMP at a particular bus in one simulation and then to find the minimum LMP in another. If we have N buses to calculate the LMP interval, 2N optimization runs should be carried out.

Given that the lower level ED is a LP problem, the bi-level model can be transformed into an MPEC by recasting the lower level problem as its KKT optimality condition [62], [63], which are later added into the upper level problem as a set of additional complementarity constraints.

$$\text{OBJ: (3.2a)} \quad (3.3a)$$

$$\text{s.t. Constraint in (3.1b), and (3.2c)} \quad (3.3b)$$

$$c_i = \lambda + \sum_{l=1}^M GSF_{l-i} \times (\mu_l^{\min} - \mu_l^{\max}) + \omega_i^{\min} - \omega_i^{\max} \quad (3.3c)$$

$$c_{wi} = \lambda + \sum_{l=1}^M GSF_{l-i} \times (\mu_l^{\min} - \mu_l^{\max}) + \varphi_i^{\min} - \varphi_i^{\max} \quad (3.3d)$$

$$0 \leq \mu_l^{\min} \perp L_l + \sum_{i=1}^N GSF_{l-i} \times (G_i + P_{wi} - D_i) \geq 0 \quad (3.3e)$$

$$0 \leq \mu_l^{\max} \perp L_l - \sum_{i=1}^N GSF_{l-i} \times (G_i + P_{wi} - D_i) \geq 0 \quad (3.3f)$$

$$0 \leq \omega_i^{\min} \perp G_i - G_i^{\min} \geq 0 \quad (3.3g)$$

$$0 \leq \omega_i^{\max} \perp G_i^{\max} - G_i \geq 0 \quad (3.3h)$$

$$0 \leq \varphi_i^{\min} \perp P_{wi} \geq 0 \quad (3.3i)$$

$$0 \leq \varphi_i^{\max} \perp P_{wi}^{\max} - P_{wi} \geq 0 \quad (3.3j)$$

With the method in [64], the complementarity constraints (3.3e)-(3.3j) can be replace by (3.4a)-(3.4l) and the MPEC problem is converted to a MILP problem.

$$0 \leq \mu_l^{\min} \leq M_{\mu}^{\min} \nu_{\mu,l}^{\min} \quad (3.4a)$$

$$0 \leq L_l + \sum_{i=1}^N GSF_{l-i} \times (G_i + P_{wi} - D_i) \leq M_{\mu}^{\min} (1 - \nu_{\mu,l}^{\min}) \quad (3.4b)$$

$$0 \leq \mu_l^{\max} \leq M_{\mu}^{\max} \nu_{\mu,l}^{\max} \quad (3.4c)$$

$$0 \leq L_l - \sum_{i=1}^N GSF_{l-i} \times (G_i + P_{wi} - D_i) \leq M_{\mu}^{\max} (1 - \nu_{\mu,l}^{\max}) \quad (3.4d)$$

$$0 \leq \omega_i^{\min} \leq M_{\omega}^{\min} \nu_{\omega,i}^{\min} \quad (3.4e)$$

$$0 \leq G_i - G_i^{\min} \leq M_{\omega}^{\min} (1 - \nu_{\omega,i}^{\min}) \quad (3.4f)$$

$$0 \leq \omega_i^{\max} \leq M_{\omega}^{\max} \nu_{\omega,i}^{\max} \quad (3.4g)$$

$$0 \leq G_i^{\max} - G_i \leq M_{\omega}^{\max} (1 - \nu_{\omega,i}^{\max}) \quad (3.4h)$$

$$0 \leq \varphi_i^{\min} \leq M_{\varphi}^{\min} \nu_{\varphi,i}^{\min} \quad (3.4i)$$

$$0 \leq P_{wi} \leq M_{\varphi}^{\min} (1 - \nu_{\varphi,i}^{\min}) \quad (3.4j)$$

$$0 \leq \varphi_i^{\max} \leq M_{\varphi}^{\max} \nu_{\varphi,i}^{\max} \quad (3.4k)$$

$$0 \leq P_{wi}^{\max} - P_{wi} \leq M_{\varphi}^{\max} (1 - \nu_{\varphi,i}^{\max}) \quad (3.4l)$$

where $M_{\mu}^{\min}$, $M_{\mu}^{\max}$, $M_{\omega}^{\min}$, $M_{\omega}^{\max}$, $M_{\phi}^{\min}$, and $M_{\phi}^{\max}$ are large enough constants, and $v_{\mu,l}^{\min}$, $v_{\mu,l}^{\max}$, $v_{\omega,l}^{\min}$, $v_{\omega,l}^{\max}$, $v_{\phi,l}^{\min}$, and $v_{\phi,l}^{\max}$ are the auxiliary binary variables [49].

3.3 Case Studies

3.3.1 PJM 5-bus System

In this section, the proposed LMP interval evaluation approach is performed on a modified PJM 5-bus system shown in Fig. 3.1. The MILP problem is solved using GAMS. Two wind power plants (WF1 and WF2) with the same capacity are added into the system at buses A and C while one original generator removed from bus A.

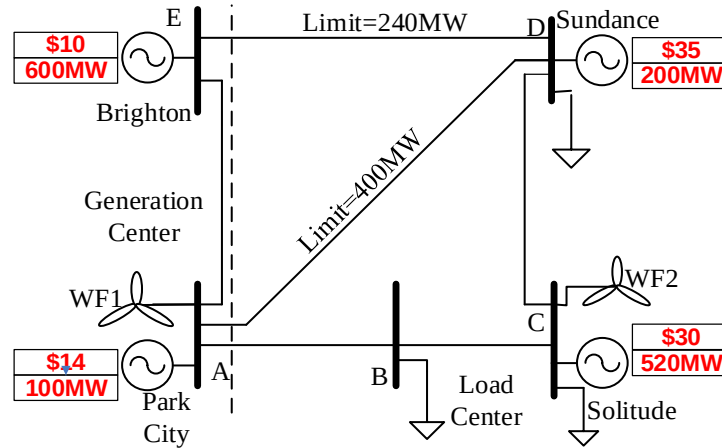


Figure 3.1 PJM 5-bus system with two wind farms

The forecast mean value of wind power is 180MW and it follows a normal distribution with a standard deviation of 10% from the mean. The total load is 1,200 MW equally distributed among buses B, C, and D. Table 3.1 shows the exact same LMP interval results from the proposed approach compared with the MC approach (with 5000 samples), while the simulation time for the proposed method and MC are 3.4 and 59.5 seconds, respectively.

Table 3.1 LMP interval results from MC method and the proposed method

Bus	LMP interval	
	Proposed	MC
A	[15.238, 16.977]	[15.238, 16.977]
B	[23.680, 28.182]	[23.680, 28.182]
C	[26.699, 30]	[26.699, 30]
D	[35, 39.943]	[35, 39.943]
E	[10, 10]	[10, 10]

3.3.2 IEEE 118-Bus System

The proposed method is also applied to a modified IEEE 118-bus system [2]. Four wind power farms are connected at buses 2, 12, 44 and 86. The mean power from each wind farm is set to 300 MW with a 10% standard deviation (σ). Fig. 3.2 shows that the same prediction results can be achieved across all buses from both approaches. However, the performance from the proposed approach is almost 20 times faster than MC approach with a moderate number of runs (5000 samples).

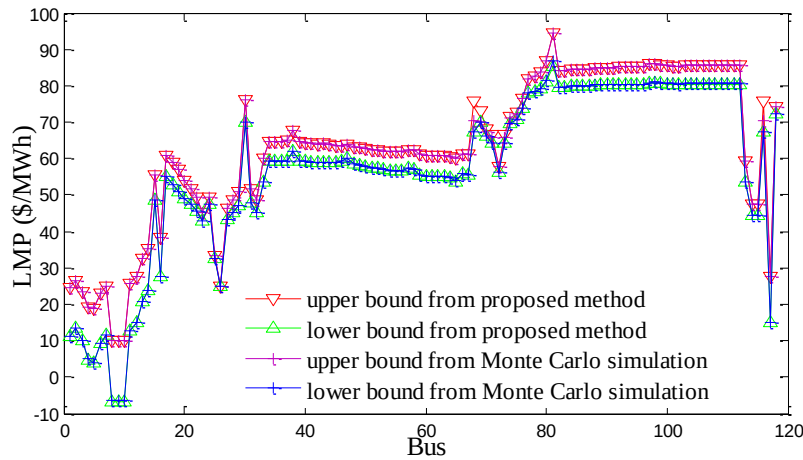


Figure 3.2 Bus LMP intervals from the proposed method and MC simulation

3.4 Conclusion

In this chapter, a bi-level optimization model is proposed to evaluate LMP intervals considering wind power uncertainty. The main contribution of this work can be summarized as follows:

1. The LMP interval problem is formulated as a bi-level optimization problem with the LMP maximization or minimization as the upper and the ISO's economic dispatch as the lower;
2. The bi-level optimization model is solved through mathematical program with equilibrium constraints (MPEC) and mixed-integer linear programming (MILP);
3. The LMP intervals can be obtained much faster than the conventional Monte Carlo Simulation method.

CHAPTER 4

COUPON BASED DEMAND RESPONSE: A STRATEGIC BIDDING

MODEL FOR LOAD SERVING ENTITIES

4.1 Introduction

The increasing demand-side participation in electricity market has presented new challenges and opportunities for the market participants [65]–[68]. For power system operators, various demand response (DR) programs have been deployed as potential resources to balance supply and demand, reduce peak-hour loads, and enhance the generation efficiency [69]. For consumers, electricity consumption is expected to be responsive to the fluctuant pricing signals to reduce their electricity payments [70]–[77]. In a fully competitive electricity market, load serving entities (LSEs) play a critical role to fill the gaps between end consumers and wholesale market operators to connect them into an optimal operation framework [78].

As a profit-seeking organization, the objective for LSEs is to maximize the expected payoff considering the uncertainty from both wholesale market and end customers. The majority of customers pay electricity bills with flat rates [79], while LSEs purchase electricity with time-varying rates from wholesale market. Naturally, LSEs will have the motivation to induce the consumers' inherent elasticity by offering DR programs [63] [64], especially when the system is under stress or close to the next binding constraint which is termed as a critical load level (CLL) in [1] [65]. This can be even more interesting with the consideration of the uncertainty due to the high penetration of wind power.

Coupon based demand response (CBDR) attempts to induce the demand flexibility in retail customers (such as small/medium size commercial, industrial, and residential customers) on

a voluntary basis [81]. In practice, LSEs have been adopting various methods, such as peak time rebate (PTR) and critical peak pricing (CPP), to realize the demand side management. However, CBDR has different features. In PTR, the rebate rates during critical periods are pre-determined and fixed whereas the coupon price is an optimization variable in CBDR. In CPP, mandatory high prices are utilized to motivate consumers to adjust their electricity consumption whereas the consumer are voluntary to participate in CBDR.

Fig. 4.1 demonstrates the impact of CBDR and wind power uncertainty to both electricity supply curve and elastic demand curve. As shown in the figure, (D_1, π_1) is the intersection between the expected supply curve and the original demand curve, and (D_2, π_4) denotes the intersection between the expected supply curve and the new demand curve with coupons. Considering the wind power output, the LMP π_1 is greater than the flat rate price η at the system demand level D_1 . If the wind power output is lower than forecasted, the LMP goes higher at π_3 ; however, if the wind generates more power than forecasted, the LMP becomes lower at π_2 . Under demand level D_1 , the expected net revenue for the LSE considering the wind uncertainty $(\eta - \pi_1) \cdot D_1$, is negative. When a coupon is provided, the elastic demand curve changes from $D_1(P)$ to $D_2(P)$. With the new demand curve, the corresponding LMP will be π_4 which is lower than the flat rate η . Consequently, as long as the net revenue $(\eta - \pi_4) \cdot D_2 - r \cdot (D_1 - D_2)$ is greater than $(\eta - \pi_1) \cdot D_1$, the LSE will have incentive to offer the coupon price r to customers in CBDR. Therefore, the CBDR program with proper coupon prices can help LSEs increase their profits by mitigating the price volatility due to wind uncertainty in wholesale market.

In competitive wholesale markets, there are two ways to implement CBDR: 1) CBDR is administered by LSEs to maximize their own profit; or 2) CBDR is administered by ISOs to maximize social welfare. Here, this chapter discusses the former one. In other words, the

customers' demand can be dispatched through CBDR by LSEs for the sake of LSEs' profit maximization.

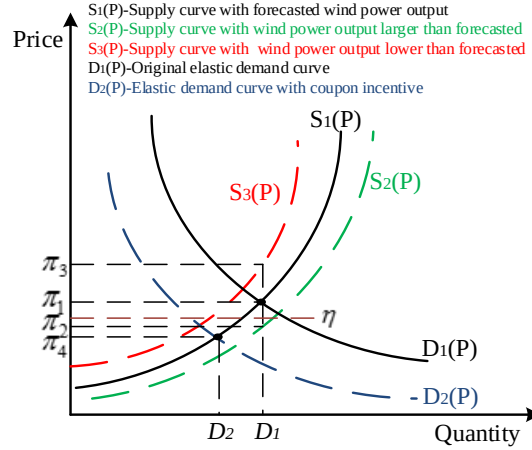


Figure 4.1 Impact of CBDR and wind power on supply and demand curves

To study the operation of an LSE under this new perspective, a strategic bidding approach considering CBDR and the wind power uncertainty is proposed in this chapter. In the proposed method, the LSE offers CBDR program to customers. Then, the range of corresponding demand reduction under the coupon is modeled. Next, the LSE aggregates all the customers' demand reduction information and mimics the ISO's electricity market-clearing procedure considering the wind power uncertainty. Hence, the LSE can obtain the optimal bidding strategy with the maximal possible expected net revenue. The final decision variables of LSEs are the coupon prices and the corresponding optimal load dispatches.

The rest of this chapter is organized as follows: Section III presents the overall bi-level model of strategic bidding for LSEs considering CBDR. Section IV discusses the baseline load and the probabilistic demand reduction models. Section V proposes the actual solution to solve the stochastic bi-level model including the procedure of transforming it into MPEC problem, and

the conversion from MPEC to MILP. Section VI demonstrates the simulation results and numerical analyses of the PJM 5-bus system and IEEE 118-bus system to clearly verify the proposed method. Section VII presents the summary and conclusion.

4.2 Strategic Bidding Model for LSEs

4.2.1 Nomenclature

N number of buses;

M number of lines;

c_i generation bidding price at bus i (\$/MWh);

G_i generation dispatch at bus i (MWh);

G_i^{max}, G_i^{min} maximum and minimum generation output at bus i ;

D_i demand at bus i (MWh);

GSF_{l-i} generation shift factor to line l from bus i ;

$Limit_l$ transmission limit of line l ;

π_i locational marginal price at bus i ;

$\eta_{i,k}$ electricity retail price for customer k at bus i (\$/MWh);

$r_{i,k}$ coupon price offered to customer k at bus i (\$/MWh);

$D_{i,k}$ energy consumption of customer k at bus i ;

$D_{i,k}^0$ energy consumption baseline of customer k at bus i ;

A bus set of the LSE strategic bidder;

B_i customer set at bus i belong to the LSE strategic bidder;

λ dual variable associated with the power balance equation in economic dispatch;

μ_l^{min}, μ_l^{max} dual variables associated with the lower and upper limits of transmission line l ;

$\omega_i^{min}, \omega_i^{max}$ dual variables associated with the lower and upper limits of the generator at bus i ;

- ψ Lagrangian function of ISO's ED problem;
- s index of wind power scenario (in superscript);
- p_s probability of wind power scenario s ;
- $P_{w,i}^s$ power output of wind farm at bus i in wind power scenario s ;
- $p_{j,d}$ probability of d th demand reduction block under the j th coupon price.

4.2.2 Procedure of LSEs' Strategic Bidding

The three-layer electricity market framework is shown in Fig. 4.2. The generation companies provide electricity offers including the available generation quantity and prices to the corresponding independent system operator (ISO), then the LSEs provide demand bids to the ISO, and finally the ISO clears the market to maximize the social welfare.

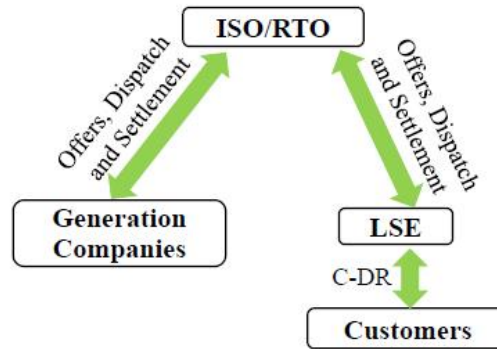


Figure 4.2 Structure of the electricity market

The illustration of LSEs' strategic bidding under this market structure will be discussed in the following subsections II-B, II-C, and II-D. Most ISOs in the U.S. implement the two-settlement system [83], [84]: day-ahead (DA) market and real-time (RT) market [85], [86]. The energy cleared in real-time markets is around 2%-8% [87] which represents a considerable with respect to the possible DR amount. With the expectation that the DA price reflects the expected

RT price, the DA market can be viewed as part of RT. Therefore, only the RT market is modeled for the LSE strategic bidding for simplicity such that this work can focus on the discussion about DR.

Figure 4.3 is the flowchart of the proposed strategic bidding for LSEs. First, LSE obtains LMPs information from ISO's DA market. Then, the LSE broadcasts the coupon price for the hours in which the LSE wants to perform CBDR to stimulate customers to reduce demand (i.e., the hours when LMP exceeds or likely to exceed the electricity flat rate). After gathering all the information of potential demand reduction, the LSE mimics ISO's economic dispatch (ED) process to identify the optimal demand reduction. Finally, the LSE performs the bidding with the revised demand.

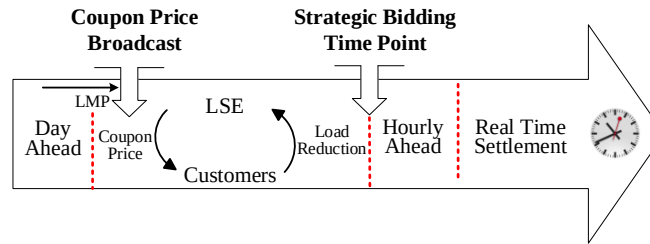


Figure 4.3 Flowchart of the proposed strategic bidding

In the above procedure, the LSE can broadcast and update the coupon price several times through communicating with customers and iteratively obtain the optimal coupon price. While in practice, the information exchange between LSEs and customers cannot be performed many times due to the huge data processing burden from numerous customers. Therefore, before broadcasting the coupon price, LSEs should be able to estimate a rough range of the optimal coupon price [88], [89] such that the iterations between LSEs and customers can be reduced and the actual updating

process of coupon price can be implemented in short term. To determine this initial optimal coupon price, the LSE can model the customers' probabilistic electricity consuming pattern under different coupon prices, then perform the strategic bidding for each coupon price, and finally obtain the optimal coupon price. The probabilistic demand reduction model will be presented in Section IV.

4.2.3 Net Revenue of LSEs

The LSE receives a gross revenue from each customer k ($k \in B_i$) at bus i ($i \in A$), as shown in k_4 to k_7 of LSE A in Fig. 4.4. This revenue is calculated as the product of the retail price $\eta_{i,k}$ and the electricity consumption $D_{i,k}$. Then, the payment (i.e., the product of spot price π_i and the electricity consumption $D_{i,k}$) is subtracted since the LSE purchases electricity from ISOs in wholesale market at volatile nodal prices. Finally, the financial incentives that the LSE pays to customers should be subtracted as well, which is the product of coupon price $r_{i,k}$ and the deviation between the actual electricity demand and the baseline electricity consumption. Therefore, the LSE's net revenue, represented by R_n , should be expressed as (4.1):

$$R_n = \sum_{i \in A} \sum_{k \in B_i} [(\eta_{i,k} - \pi_i) \times D_{i,k} - r_{i,k} \times (D_{i,k}^0 - D_{i,k})] \quad (4.1)$$

The LMP π_i in (4.1) is obtained from ISO's ED [81], and the LMP formulation will be discussed in subsection II-C.

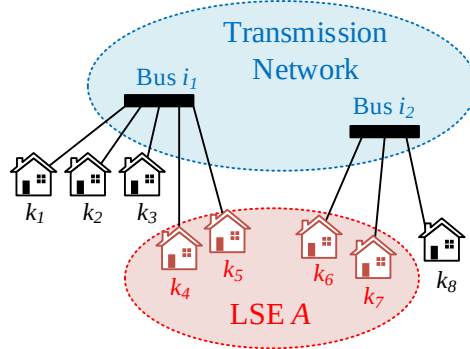


Figure 4.4 The illustrative figure of a LSE and its customers

4.2.4 ISO's Economic Dispatch

ED is carried out by ISOs to clear the market as well as determining LMPs and generation dispatches. As the CBDR program is between LSEs and customers, the demands in the ISOs' ED model holds no elasticity.

Here a fixed transmission network is assumed with a linearized, lossless DC model, and generations are considered fully competitive and rational in bidding at their marginal costs [90], [91]. This is aligned with various DC optimal power flow (DCOPF) models utilized by many ISOs [69]. Also, wind and DR are considered in terms of modeling the uncertainty, while other sources of uncertainty can be added if needed [70].

Therefore, the DCOPF approach is employed here to model the electricity market and estimate LMPs. While the actual models in practice are more complex, due to the need of computation robustness and efficiency, the ED based on DCOPF is utilized here to illustrate the main point of the proposed work. The DCOPF is essentially a linear programming (LP) problem given by:

$$\min \sum_{i=1}^N c_i \times G_i \quad (4.2a)$$

$$\text{s.t. } \sum_{i=1}^N G_i = \sum_{i=1}^N D_i : \lambda \quad (4.2b)$$

$$D_i = \sum_{k \in B_i} D_{i,k}, \forall i \in A \quad (4.2c)$$

$$\begin{aligned} -\text{Limit}_l &\leq \sum_{i=1}^N GSF_{l-i} \times (G_i - D_i) \leq \text{Limit}_l : \\ \mu_l^{\min}, \mu_l^{\max}, \forall l &= 1, 2, \dots, M \end{aligned} \quad (4.2d)$$

$$G_i^{\min} \leq G_i \leq G_i^{\max} : \omega_i^{\min}, \omega_i^{\max}, \forall i = 1, 2, \dots, N \quad (4.2e)$$

After obtaining the optimal solution of the above ED, the LMP π_i can be calculated with the Lagrangian function. This function and LMP can be written as:

$$\begin{aligned} \psi = & \left(\sum_{i=1}^N c_i \times G_i \right) - \lambda \left(\sum_{i=1}^N G_i - \sum_{i=1}^N D_i \right) \\ & - \sum_{l=1}^M \mu_l^{\min} \left(\sum_{i=1}^N GSF_{l-i} \times (G_i - D_i) + \text{Limit}_l \right) \\ & - \sum_{l=1}^M \mu_l^{\max} \left(\text{Limit}_l - \sum_{i=1}^N GSF_{l-i} \times (G_i - D_i) \right) \\ & - \sum_{i=1}^N \omega_i^{\min} (G_i - G_i^{\min}) - \sum_{i=1}^N \omega_i^{\max} (G_i^{\max} - G_i) \end{aligned} \quad (4.2f)$$

$$\pi_i = \frac{\partial \psi}{\partial D_i} = \lambda + \sum_{l=1}^M GSF_{l-i} (\mu_l^{\min} - \mu_l^{\max}) \quad (4.2g)$$

4.2.5 Bi-level Model of Strategic Bidding

In the bidding process, the decision variables are the coupon prices ($r_{i,k}$) and the corresponding demand dispatches ($D_{i,k}$). Since the LMP depends on ISO's ED in (4.2a)-(4.2e), the strategic bidding problem is formulated as a bi-level problem. The upper level is to maximize the LSE's profit in (4.1), and the lower level is to minimize the generation cost to model the ISO's market-clearing process [92]. The bi-level strategic bidding model is given by:

$$\max \sum_{i \in A} \left(\sum_{k \in B_i} (\eta_{i,k} \times D_{i,k} - r_{i,k} \times (D_{i,k}^0 - D_{i,k})) - \pi_i \times D_i \right) \quad (4.3a)$$

$$\text{s.t. } D_{i,k}^{\min} \leq D_{i,k} \leq D_{i,k}^{\max}, \forall i \in A, k \in B_i \quad (4.3b)$$

$$\text{where } \pi_i, \forall i \in \arg\{(4.2a) - (4.2e), (4.2g)\} \quad (4.3c)$$

where $D_{i,kmin}$ and $D_{i,kmax}$ are the minimum and maximum demand values, respectively, of demand k at bus i . B_i is the set of customers on bus i which have the CBDR with this LSE. The LMP π_i from the ED depends on the demand, $D_{i,k}$, as well as the bid prices/quantities of generators.

Note that both the coupon price and the LSE's demand are decision variables in the bidding process and the objective function is nonlinear. To solve the strategic model in (4.3a) to (4.3c), it is necessary to discuss the demand model first. Therefore, Section IV covers the baseline model and a probabilistic demand reduction model which gives the probabilistic distribution of demand reduction under a specific coupon price. Since $r_{i,k} \times (D_{i,k}^0 - D_{i,k})$ is linear with a specific (given) coupon price, $D_{i,k}$ in (4.3a)-(4.3c) can be solved for a specific $r_{i,k}$ using the mathematic algorithm presented in subsections V.A to V.C, with different wind scenarios considered. Then, subsection V.D discusses the overall process to choose the optimal coupon price.

4.3 Baseline Demand and Probabilistic Demand Reduction

4.3.1 Baseline Demand Model

The CBDR programs are critically dependent on the customers' demand baseline [93] from which the demand reduction in DR can be calculated. Due to the strong cyclic pattern of customers' electricity consumption over time [94], the demand baseline can be obtained from historical data. For instance, Southern California Edison (SCE) employs an approach called "10-Day Average Baseline" [95]. More details concerning the baseline calculation have been

introduced in [96], though it is out of the research scope of this chapter to discuss the pros and cons of various consumer demand baseline methods.

4.3.2 Probabilistic Residential Demand Reduction Model

As previously discussed, the uncertainty of customers' demand reduction is typically modeled as follows in CBDR based strategic bidding: 1) a LSE offers a coupon price to its customers; 2) the customers provide the range of corresponding demand reduction to the LSE; 3) the LSE calculates its expected net revenue through bidding this revised demand in the ISO's electricity market; and 4) by repeating steps 1)-3) with different coupon prices, the optimal coupon price, which brings the LSE the maximum net revenue, can be found.

However, there are two potential challenges for this process: 1) it is rarely feasible to keep frequently updating customers' demand reduction data; and 2) interaction with numerous customers makes it too time-consuming to serve as an online implementation. Therefore, a practical and validated probabilistic model of demand reduction under different coupon prices is established in this chapter. The schematic information flow is shown in Fig. 5, where the inputs of the model are the coupon price, the CBDR's location and time length. The figure also shows that the output is the corresponding probabilistic distribution of demand reduction. The procedure to generate this model can be summarized as follows:

Step1) Based on the given location to be studied, the residents will be categorized into several groups ($G_1, G_2, \dots, G_N$) based on their demographic information. For each group of residents, step 2) to 5) will be performed.

Step2) For group G_i , the types and ratings of their appliances can be obtained by analyzing Residential Energy Consumption Survey (RECS) [97] by the U.S. Energy Information Administration (EIA).

Step3) For group Gi, the American Time Use Survey (ATUS) [98] by the U.S. Department of Labor can provide what are the current activities of residents.

Step4) In order to study customers' reactions to financial incentives, the Center for Ultra-wide-area Resilient Electric Energy Transmission Networks (CURENT) [99] has collected self-reported data from 711 U.S. residents across 48 states in 2013. This study estimated the adopting rates of major DR behaviors as a function of the demanded financial rewards.¹ Therefore, based on the results of this survey, the attitude distribution of group Gi towards DR with given coupon price can be estimated.

Step5) With the integration of the appliances information and the activities that those residents are performing, the potential demand reduction can be obtained.

Step6) Given the residents' attitude towards different coupons, their possible demand reduction activity can be modeled. As long as the residents' attitude distribution and the potential reducible demand of all the groups are known, it is easy to obtain the probabilistic distribution of the demand reduction.

In summary, the model proposed above evaluates the characteristics of residential demand reduction under CBDR programs based on the residents' portfolios and provides the probability distribution of demand reduction for given times, locations, and coupon prices.

This survey study was conducted through Amazon's Mechanical Turk (MTurk). MTurk is a crowdsourcing Internet market place which enables researchers and companies to collect data on human intelligence tasks. MTurk has been received great popularity among social scientists as a useful research tool to collect data [100]. The survey was published on MTurk as a "hit." The respondents on MTurk read the instructions and a brief description of this survey and decide whether to accept the hit. Respondents could stop answering the survey questions at any point by

choosing to “return the hit.” Once a respondent has completed the hit, he or she will receive a payment via Amazon, which can be delivered as a gift certificate or transferred to a U.S. bank account.

Here, several simulation results of a typical scenario have been tested to demonstrate the model features. Figure 4.6 shows the probability distribution of reduced power ratio (RPR) with various coupon prices. The characteristics of residential loads at a given coupon price for 24 hours are illustrated in Fig. 4.7. Furthermore, the residential load model varies with different resident portfolios. For example, the probability distribution of RPR for 24 hours is significantly different for Northeast, Midwest, South, and West regions, as shown in Fig. 4.8. According to Fig. 4.9, the customers’ responses towards different coupon prices vary as well.

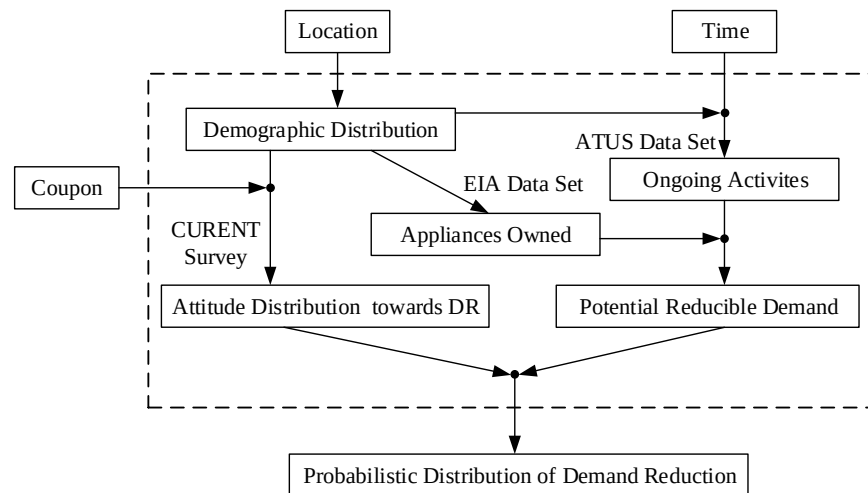


Figure 4.5 Schematic figure of information flow for residential demand reduction modeling

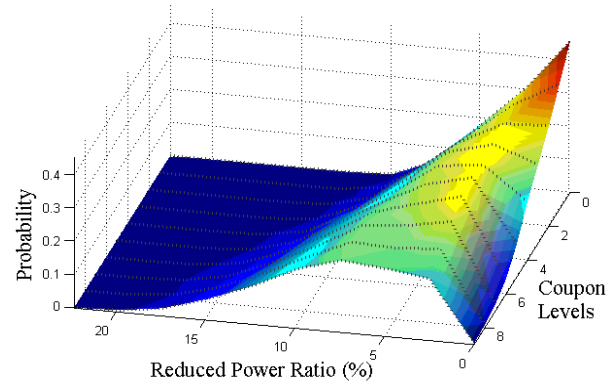


Figure 4.6 Probability distribution of RPR under different coupon prices

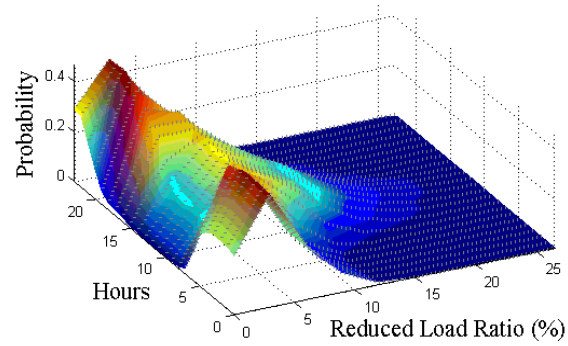


Figure 4.7 Probability distribution of 24-hour RPR

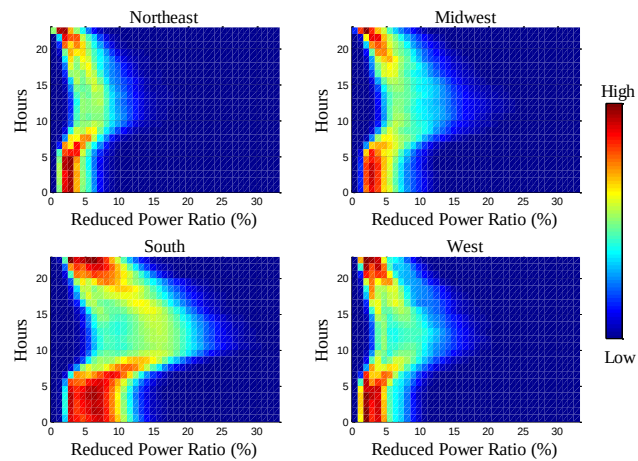


Figure 4.8 Probability distribution of 24-hour RPR in different areas

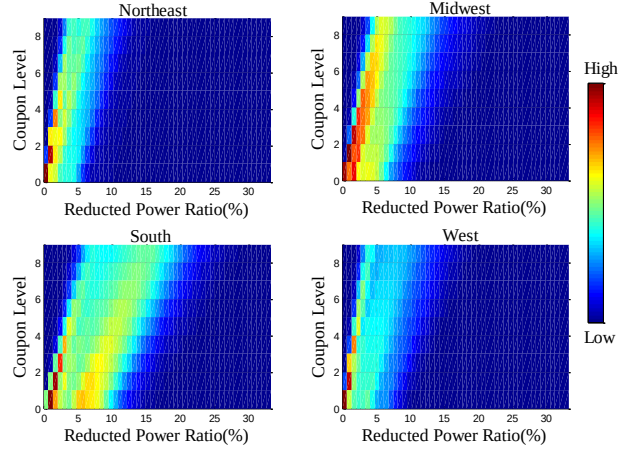


Figure 4.9 Probability distribution of RPR under different coupon prices in different areas

The aforementioned results of the preliminary study regarding residential demand modeling are reasonable, and they can verify the validation of the proposed model. Therefore, this model has been implemented to simulate the uncertainty of customers' behaviors to further formulate the strategic bidding problem.

4.4 Mathematical Solution of the Proposed Model

As introduced in Section III, the strategic bidding problem in (4.3a) to (4.3c) is a bi-level optimization problem. Because of the existence of dependent variables in each level, these two optimization problems are coupled. For instance, the LMP in the upper level problem is decided by the lower level problem of ISO's market clearing, while the demands at load buses of LSE bidders in the lower level market clearing problem depends on the upper level. In this chapter, DCOPF is implemented to clear the ISO's market. Due to the linearity of DCOPF [90], [101], its optimal solution should be a unique point that satisfies the Karush-Kuhn-Tucher (KKT) optimality conditions. Consequently, the bi-level optimization problem is formulated as a mathematical program with equilibrium constraints (MPEC) by integrating the lower level problem into the upper level problem using its KKT conditions as the extra complimentary

constraints [91], [102], [103]. According to the strong duality theory [103]–[105], this MPEC model can be converted to a MILP that is solvable by available software.

4.4.1 Formulation as a MPEC

Given that the lower level ED is a LP problem, the bi-level strategic bidding model can be transformed to a MPEC by recasting the lower level problem as its KKT optimality condition, then adding them into the upper level problem as a set of additional complimentary constraints.

$$\max (4.3a) \tag{4.4a}$$

$$\text{s.t. Constraint in (4.2b), (4.2g) and (4.3b)} \tag{4.4b}$$

$$c_i = \lambda + \sum_{l=1}^M GSF_{l-i} \times (\mu_l^{\min} - \mu_l^{\max}) + \omega_i^{\min} - \omega_i^{\max} \tag{4.4c}$$

$$0 \leq \mu_i^{\min} \perp Limit_i + \sum_{i=1}^N GSF_{l-i} \times (G_i - D_i) \geq 0 \tag{4.4d}$$

$$0 \leq \mu_i^{\max} \perp Limit_i - \sum_{i=1}^N GSF_{l-i} \times (G_i - D_i) \geq 0 \tag{4.4e}$$

$$0 \leq \omega_i^{\min} \perp G_i - G_i^{\min} \geq 0 \tag{4.4f}$$

$$0 \leq \omega_i^{\max} \perp G_i^{\max} - G_i \geq 0 \tag{4.4g}$$

4.4.2 Mixed-integer Linear Programming (MILP)

The MPEC model in (4.4a)-(4.4g) is nonlinear due to the product term $\pi_i \cdot D_{i,k}$ in the objective function and the complementarity constraints (4.4d)-(4.4g). The linearization for them is presented below.

According to the strong duality theory, the objective of the primal problem is equal to the objective of the corresponding dual problem. For the ED problem, the relationship between the objectives of the dual and primal problems can be expressed as follows:

$$\begin{aligned}
& \lambda \times \sum_{i=1}^N D_i + \sum_{l=1}^M \mu_l^{\max} \times (-Limit_l - \sum_{i=1}^N GSF_{l-i} \times D_i) \\
& + \sum_{l=1}^M \mu_l^{\min} \times (-Limit_l + \sum_{i=1}^N GSF_{l-i} \times D_i) \\
& + \sum_{i=1}^N \omega_i^{\max} \times (-G_i^{\max}) + \sum_{i=1}^N \omega_i^{\min} \times (G_i^{\min}) \\
& = \sum_{i=1}^N c_i \times G_i
\end{aligned} \tag{4.5}$$

From the LMP expression in (4.2f), the product term $\pi_i \cdot D_i$ in (4.3a) can be transformed as (4.6).

$$\sum_{i \in A} \pi_i \times D_i = \lambda \times \sum_{i \in A} D_i + \sum_{l=1}^M \sum_{i \in A} GSF_{l-i} (\mu_l^{\min} - \mu_l^{\max}) \times D_i \tag{4.6}$$

Note, (4.6) describes D_i ($i \in A$) which is about the demand at the bus within LSE, while (4.5) is about all buses in the system. Taking (4.6) into (4.5), we have

$$\begin{aligned}
& \sum_{i \in A} \pi_i \times D_i + \lambda \times \sum_{i \in A} D_i + \sum_{l=1}^M \mu_l^{\max} \times (-Limit_l - \sum_{i \notin A} GSF_{l-i} \times D_i) \\
& + \sum_{l=1}^M \mu_l^{\min} \times (-Limit_l + \sum_{i \notin A} GSF_{l-i} \times D_i) \\
& + \sum_{i=1}^N \omega_i^{\max} \times (-G_i^{\max}) + \sum_{i=1}^N \omega_i^{\min} \times (G_i^{\min}) \\
& = \sum_{i=1}^N c_i \times G_i
\end{aligned} \tag{4.7}$$

where D_i ($i \notin A$) is the demand on the bus which does not belong to the LSE bidder and it is assumed that the demands on these buses are constant for simplicity. Also, a strategic bidder can include a set of probabilistic scenarios to represent the other LSEs' demand uncertainty.

Therefore, based on (4.7), we can replace the $\sum_{i \in A} \pi_i \times D_i$ item in the objective function (4.3a) to form (4.8a), which is shown below. Thus, the MPEC problem is converted to a MILP problem given by:

$$\begin{aligned}
& \max \sum_{i \in A} \sum_{k \in B_i} (\eta_{i,k} \times D_{i,k} - r_{i,k} \times (D_{i,k}^0 - D_{i,k})) \\
& - \sum_{i=1}^N c_i \times G_i + \lambda \times \sum_{i \notin A} D_i \\
& + \sum_{l=1}^M \mu_l^{\max} \times (-Limit_l - \sum_{i \notin A} GSF_{l-i} \times D_i) \\
& + \sum_{l=1}^M \mu_l^{\min} \times (-Limit_l + \sum_{i \notin A} GSF_{l-i} \times D_i) \\
& + \sum_{i=1}^N \omega_i^{\max} \times (-G_i^{\max}) + \sum_{i=1}^N \omega_i^{\min} \times (G_i^{\min})
\end{aligned} \tag{4.8a}$$

$$\text{s.t. Constraints in (4.4b) and (4.4c)} \tag{4.8b}$$

$$0 \leq \mu_l^{\min} \leq M_{\mu}^{\min} \nu_{\mu,l}^{\min} \tag{4.8c}$$

$$0 \leq Limit_l + \sum_{i=1}^N GSF_{l-i} \times (G_i - D_i) \leq M_{\mu}^{\min} (1 - \nu_{\mu,l}^{\min}) \tag{4.8d}$$

$$0 \leq \mu_l^{\max} \leq M_{\mu}^{\max} \nu_{\mu,l}^{\max} \tag{4.8e}$$

$$0 \leq Limit_l - \sum_{i=1}^N GSF_{l-i} \times (G_i - D_i) \leq M_{\mu}^{\max} (1 - \nu_{\mu,l}^{\max}) \tag{4.8f}$$

$$0 \leq \omega_i^{\min} \leq M_{\omega}^{\min} \nu_{\omega,i}^{\min} \tag{4.8g}$$

$$0 \leq G_i - G_i^{\min} \leq M_{\omega}^{\min} (1 - \nu_{\omega,i}^{\min}) \tag{4.8h}$$

$$0 \leq \omega_i^{\max} \leq M_{\omega}^{\max} \nu_{\omega,i}^{\max} \tag{4.8i}$$

$$0 \leq G_i^{\max} - G_i \leq M_{\omega}^{\max} (1 - \nu_{\omega,i}^{\max}) \tag{4.8j}$$

where $M_{\mu}^{\min}$, $M_{\mu}^{\max}$, $M_{\omega}^{\min}$, and $M_{\omega}^{\max}$ are large enough constants, and $\nu_{\mu,l}^{\min}$, $\nu_{\mu,l}^{\max}$, $\nu_{\omega,i}^{\min}$, and $\nu_{\omega,i}^{\max}$ are the auxiliary binary variables [64].

4.4.3 Model Extensions to Integrate Wind Power

In this subsection, the extensions of the above model, including the uncertainty of wind power, is discussed. The forecasted wind power production is expressed as a set of probabilistic scenarios ($s = 1 \sim S$) with a probability set of $\{p_s\}$. The model below in (4.9a)-(4.9f) is an example of an ED model that includes wind power for one scenario.

$$\min \sum_{i=1}^N c_i \times G_i^s \quad (4.9a)$$

$$\text{s.t. } \sum_{i=1}^N (G_i^s + P_{W,i}^s) = \sum_{i=1}^N D_i : \lambda^s \quad (4.9b)$$

$$D_i = \sum_{k \in B_i} D_{i,k}, \forall i \in A \quad (4.9c)$$

$$-Limit_l \leq \sum_{i=1}^N GSF_{l-i} \times (G_i^s + P_{W,i}^s - D_i) \leq Limit_l : \quad (4.9d)$$

$$\mu_l^{s,\min}, \mu_l^{s,\max}, \forall l = 1, 2, \dots, M$$

$$G_i^{\min} \leq G_i^s \leq G_i^{\max} : \omega_i^{s,\min}, \omega_i^{s,\max}, \forall i = 1, 2, \dots, N \quad (4.9e)$$

where G_i^s is the generation dispatch at bus i (MWh) under the s th wind scenario.

The LMP is given by

$$\pi_i^s = \lambda^s + \sum_{l=1}^M GSF_{l-i} (\mu_l^{s,\min} - \mu_l^{s,\max}) \quad (4.9f)$$

Therefore, the LSE's net revenue can be formulated as (4.10a) and then transformed to (4.10b). The constraints are modelled in (4.10c) to (4.10l).

$$\max \sum_{i \in A} \left(\sum_{k \in B_i} (\eta_{i,k} \times D_{i,k} - r_{i,k} \times (D_{i,k}^0 - D_{i,k})) \right) - \sum_{s=1}^S p_s \times \pi_i^s \times D_i \quad (4.10a)$$

$$\begin{aligned}
& \max \sum_{i \in A} \sum_{k \in B_i} (\eta_{i,k} \times D_{i,k} - r_{i,k} \times (D_{i,k}^0 - D_{i,k})) \\
& - \sum_{s=1}^S p_s \times \left\{ \sum_{i=1}^N c_i \times G_i^s - \lambda^s \times \left(\sum_{i \notin A} D_i - \sum_{i=1}^N P_{W,i}^s \right) \right. \\
& - \sum_{l=1}^M \mu_l^{s,\max} \times [-Limit_l + \sum_{i=1}^N GSF_{l-i} \times P_{W,i}^s \\
& - \sum_{i \notin A} GSF_{l-i} \times D_i] - \sum_{l=1}^M \mu_l^{s,\min} \times [-Limit_l \\
& - \sum_{i=1}^N GSF_{l-i} \times P_{W,i}^s + \sum_{i \notin A} GSF_{l-i} \times D_i] \\
& \left. - \sum_{i=1}^N \omega_i^{s,\max} \times (-G_i^{\max}) - \sum_{i=1}^N \omega_i^{s,\min} \times (G_i^{\min}) \right\}
\end{aligned} \tag{4.10b}$$

$$\text{s.t. Constraints in (4.3b) and (4.9b)} \tag{4.10c}$$

$$c_i = \lambda^s + \sum_{l=1}^M GSF_{l-i} \times (\mu_l^{s,\min} - \mu_l^{s,\max}) + \omega_i^{s,\min} - \omega_i^{s,\max} \tag{4.10d}$$

$$0 \leq \mu_l^{s,\min} \leq M_{\mu}^{\min} \nu_{\mu,l}^{s,\min} \tag{4.10e}$$

$$0 \leq Limit_l + \sum_{i=1}^N GSF_{l-i} \times (G_i^s + P_{W,i}^s - D_i) \leq M_{\mu}^{\min} (1 - \nu_{\mu,l}^{s,\min}) \tag{4.10f}$$

$$0 \leq \mu_l^{s,\max} \leq M_{\mu}^{\max} \nu_{\mu,l}^{s,\max} \tag{4.10g}$$

$$0 \leq Limit_l - \sum_{i=1}^N GSF_{l-i} \times (G_i^s + P_{W,i}^s - D_i) \leq M_{\mu}^{\max} (1 - \nu_{\mu,l}^{s,\max}) \tag{4.10h}$$

$$0 \leq \omega_i^{s,\min} \leq M_{\omega}^{\min} \nu_{\omega,i}^{s,\min} \tag{4.10i}$$

$$0 \leq G_i^s - G_i^{\min} \leq M_{\omega}^{\min} (1 - \nu_{\omega,i}^{s,\min}) \tag{4.10j}$$

$$0 \leq \omega_i^{s,\max} \leq M_{\omega}^{\max} \nu_{\omega,i}^{s,\max} \tag{4.10k}$$

$$0 \leq G_i^{\max} - G_i^s \leq M_{\omega}^{\max} (1 - \nu_{\omega,i}^{s,\max}) \tag{4.10l}$$

4.4.4 Demand Uncertainty under Different Coupon Prices

The optimization models (4.4a)-(4.4g), (4.8a)-(4.8j), and (4.10a)-(4.10l) above give the LSE's net revenue and optimal demand dispatch under the specific coupon price and demand reduction level [Dimin, Dimax]. However, the LSE still need to obtain the optimal coupon price. Based on the probabilistic model of demand reduction with the coupon presented in Section III, the customers will have different behavior patterns responding to the CBDR program with different coupon prices. Here, the expected net revenue (ENR) is defined as an indicator for the LSE bidder to determine the most profitable coupon price. The ENR under the j th coupon price is:

$$ENR_j = \sum_{d=1}^{N^d} p_{j,d} \times R_{n,j,d} \quad (4.11)$$

where $R_{n,j,d}$ is the LSE's net revenue in the d th demand reduction block under the j th coupon price which can be obtained through the model (4.10b)-(4.10l) presented in previous sections. When all ENR under different coupon prices are obtained, the LSE can choose the optimal coupon price with the maximum ENR and the corresponding demand dispatch. It should be noted that although the demand uncertainty under a specific coupon price can be model in the optimization model (4.10b)-(4.10l) using the similar approach to the wind uncertainty, the whole model built in that way will be dimensionally more complex. For instance, if n wind scenarios and m demand reduction blocks under a coupon price are considered, the whole model contains $n \times m$ sets of variables and constraints for the lower level ISO's ED problem. Therefore, the discretized decomposition using Equation (4.11) and the optimization algorithm in (4.10b)-(4.10l) is straightforward and easy to solve.

4.4.5 Overall Procedure

To better illustrate the proposed strategic bidding model for LSE, the flowchart of the overall procedure is shown in Fig. 4.10 and described next. According to the probabilistic demand reduction model proposed in Section IV, the demand reduction is subject to a probabilistic distribution with different coupon prices as shown in Fig. 4.6 and Fig. 4.9. For any given coupon price, the proposed model generates a set of discretized range of demand reduction and the corresponding probability. Then, the optimization model in (4.10b)-(4.10l) can provide the amount of profit under a specific demand reduction range with multiple probabilistic wind scenarios considered. Hence, the LSE's expected profit can be obtained by summing up the profits under different demand reduction ranges multiplied by corresponding probability weights, as shown in (4.11). Finally, the optimal coupon price can be found with a comparison of the LSE's ENR profits at different coupon prices to find the best ENR.

It should be noted that if more than one LSEs behave strategically in the market according to the model proposed in this chapter, the resulting model is an equilibrium problem with equilibrium constraints (EPEC) [106]. Another concern associated with multiple LSEs performing DR is that the LSEs may implement different types of DR programs such that it may not be realistic to perform this CBDR based strategic bidding for all the LSEs in the electricity market. These can be future research topics.

4.5 Case Studies

In this section, the proposed strategic bidding approach is performed on a modified PJM 5-bus system [107], which is chosen for the easiness to illustrate the concept and to verify by the audience. Another case study is performed on the IEEE 118-bus system to further validate the

proposed method. The MILP problem is solved by CPLEX 12.6 [108] under GAMS [54] on a DELL laptop with dual Core-i5 processors clocking at 2.6 GHz and 4 GB of RAM.

4.5.1 PJM 5-Bus Test System

The test system is modified from the PJM 5-bus system. The system parameters are from [90]. Two wind power plants (WF1 and WF2) with the same generation capacity are added into the system at buses A and C, while one of two original generators at bus A is removed. The total load is equally distributed between buses B, C, and D. The modified system is depicted in Fig. 4.11.

In the case study, the LSE bidder is located at bus D. The flat electricity rate offered to the customers at bus D by the LSE is set as \$20/MWh. This study also assumes that the highest coupon price is no more than 50% of the flat electricity rate. Hence, the coupon price varies between \$0/MWh to \$10/MWh with \$1/MWh as the incremental step. Hence, there are 11 different levels which are aligned with the 11 probabilistic levels of demand reduction in the survey data obtained in [97]–[99].

4.5.2 Implication at Different Load Levels

In this subsection, five representative operating points (cases 1-5) at different system load levels (CLLs) are chosen to investigate the implication for DR at different load levels. The wind power generation model in [109] is implemented in the case study.

The five load levels are chosen based on the critical load level concept which represents a binding constraint at a particular system load level [90], [101]. As shown in Fig. 4.12, the left-center diagram shows the five cases at different load levels with the “X” symbols in the LMP versus load curve, which is obtained with probabilistic wind power scenarios. The corresponding demand dispatches under the optimal coupon price for each operating point are listed in Table 4.1.

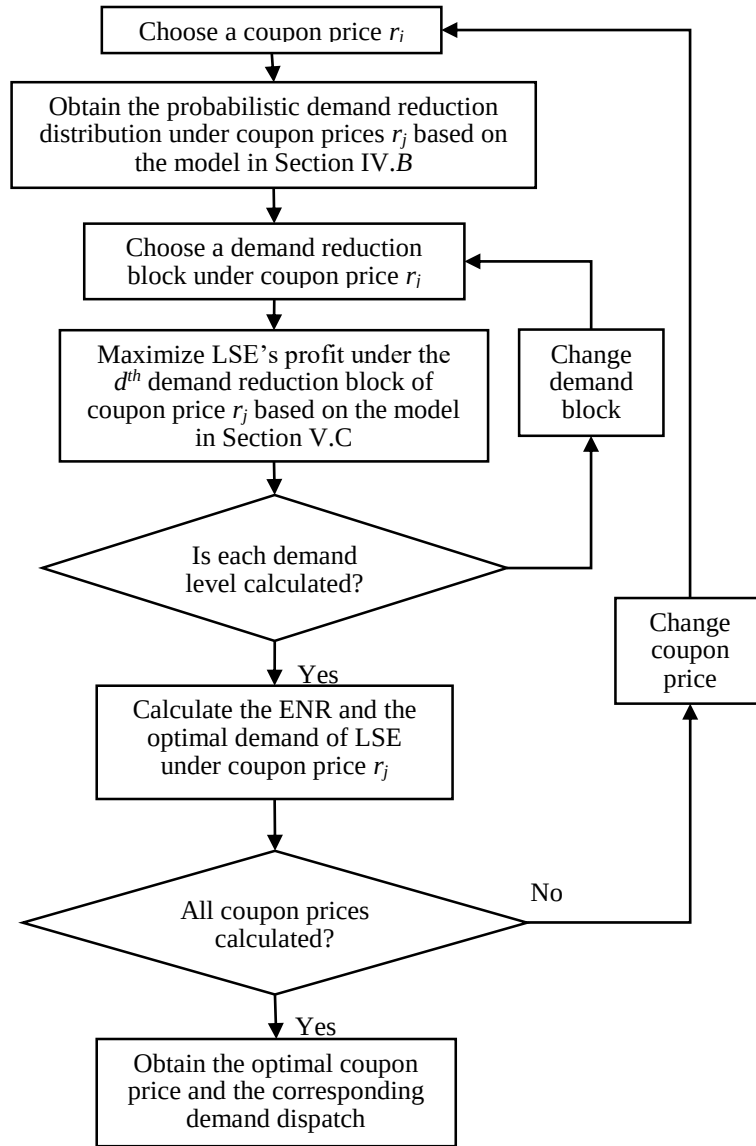


Figure 4.10 The flowchart of the proposed strategic bidding model

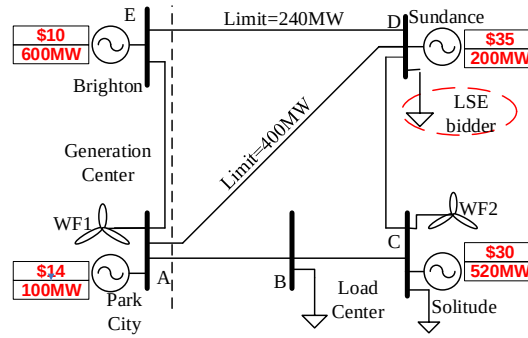


Figure 4.11 PJM 5-bus system with two wind farms

Table 4.1 DR results under different operating points

Cases	Load at Bus D (MW)	ENR w/o DR	Exp LMP w/o DR	ENR w/ DR	Exp LMP w/ DR	Coupon (\$/MWh)	Dispatched Load (MW)
Case 1	266	2660	10	2660	10.00	0	266.0
Case 2	290	2510	11.346	2670	10.40	4	281.3
Case 3	300	-61.4	20.205	2089	11.60	10	276.6
Case 4	320	-4684	34.638	-2358	26.80	10	290.9
Case 5	350	-5250	35	-5048	34.99	6	327.7

The curves of changed ENR (or ΔENR) with CBDR for the five case studies are shown in Fig. 4.12. Again, the coupon range is between \$1/MWh and \$10/MWh corresponding to the ten probabilistic demand reduction levels.

It can be observed that the patterns of five case studies are different. Case 1 demonstrates that when the current operating point is not close to a CLL (i.e., the next binding constraint when the load increases) and the corresponding LMP is lower than the flat rate, the ΔENR is negative which implies that LSE has no incentive to implement CBDR at this operating point.

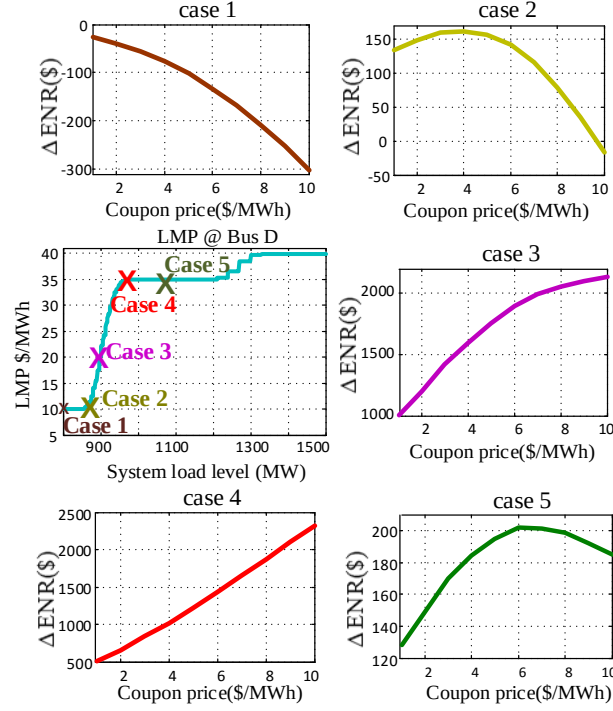


Figure 4.12 ΔENR versus coupon price on five typical operating points

In contrast, the ΔENR is positive for each of the other four cases, which means an increased profit of LSE with CBDR. Meanwhile, the pattern of ΔENR versus coupon price varies for these four cases 2-5. In Cases 3 and 4, ΔENR versus coupon price continuously increases in the range of [1, 10] \$/MWh, while ΔENR versus coupon price in Cases 2 and 5 increases and then decreases. The pattern is analyzed as follows. First, the ENR is related to the LSE payment to ISO, which is the product of price and demand (i.e., $\pi \cdot D$). Therefore, when the operating point is considerably greater than the previous CLL as in Cases 2 and 5, any reduction of demand does not give much reduction in the price, as also shown in Table 4.1. In contrast, in Cases 3 and 4, a reduction in demand will lead to considerably reduction in price as well, so the total reduced payment to ISO or ΔENR is somewhat quadratic to coupon price and dominates the coupon paid to customers. So, the ΔENR versus coupon price curve is monotonically increasing in Cases 3 or

4; however, in Cases 2 and 5, the curves increase when the coupon price is low, and then decrease when the coupon price is high which implies the coupon is too costly if compared with demand reduction because the price does not change much.

4.5.3 Impact from Wind Power Capacity

Various scenarios have been simulated to investigate the impacts of wind power from two aspects: 1) wind power capacity, and 2) wind power forecast uncertainty. This subsection discusses the wind power capacity, and the next subsection discusses about the impact from wind power uncertainty.

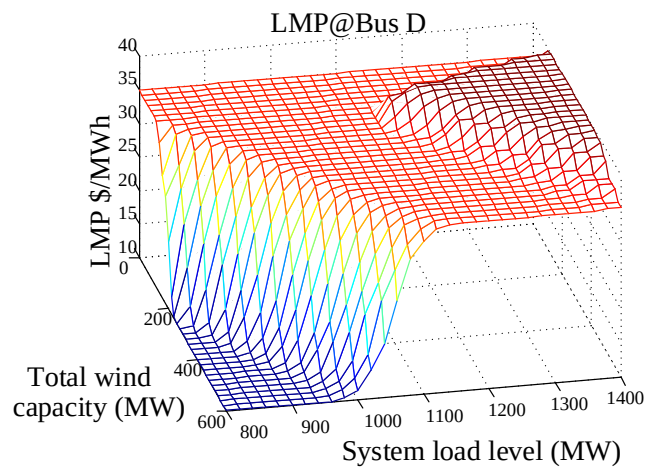


Figure 4.13 LMP versus different load levels with various wind capacity integrated into PJM 5-bus system

As illustrated in Fig. 4.13, the simulation results with total wind power capacity from 0 to 600MW show that the staircase curve of LMP holds the same pattern while the CLLs vary. Consequently, the typical operating points for each specific case change in accordance with wind

power capacities. The results of ΔENR versus coupon price under three different wind capacities (320, 360, and 400 MW) are graphed in Fig. 4.14.

It can be observed from Fig. 4.14 that in the same case, the curves of ΔENR versus coupon price hold similar patterns to the previous case study in subsection V-B, despite the differences in wind capacities. Therefore, the wind penetration does not change the ΔENR versus coupon price pattern with respect to a specific case. As a matter of fact, the operating point with respect to CLL will determine the pattern of ΔENR versus coupon price.

4.5.4 Wind Power Forecast Uncertainty

Figure 4.15 shows the impact of wind power forecast uncertainty to the ΔENR by implementing the CBDR program at five load levels (LL1 - LL5). Table 4.2 shows the simulation parameters. Figure 4.16 is the staircase LMP curves under various wind power forecast uncertainty.

According to Fig. 4.15, at LL3 and LL4, CBDR helps the LSE to gain a significant amount of ΔENR when σ is low; however, ΔENR decreases when σ , the indicator of wind power forecast uncertainty, increases. The reason is that the LMP sensitivity at LL3 and LL4 decreases when uncertainty increase demonstrated in Fig. 4.16 (i.e., the slope of LMP decreases when σ increases.) Consequently, a higher uncertainty leads to lower LMP variations and smaller values of ΔENR .

Table 4.2 Parameters in Wind Uncertainty Test

Wind Speed Model	Normal Distributed
WF1 Wind Power Mean (MW)	180
WF2 Wind Power Mean (MW)	180
σ , Wind Speed Standard Deviation	0~0.4

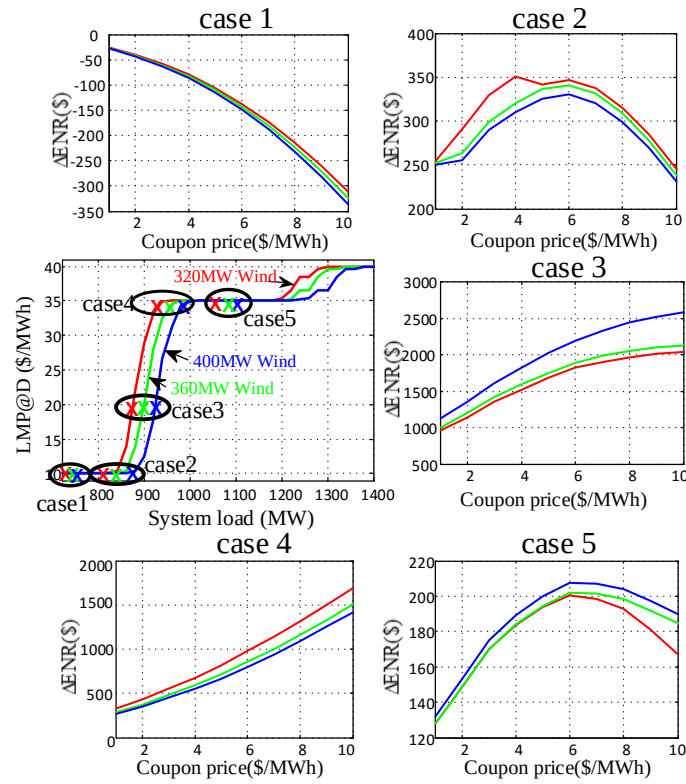


Figure 4.114 Δ ENR versus coupon price with different wind power capacities

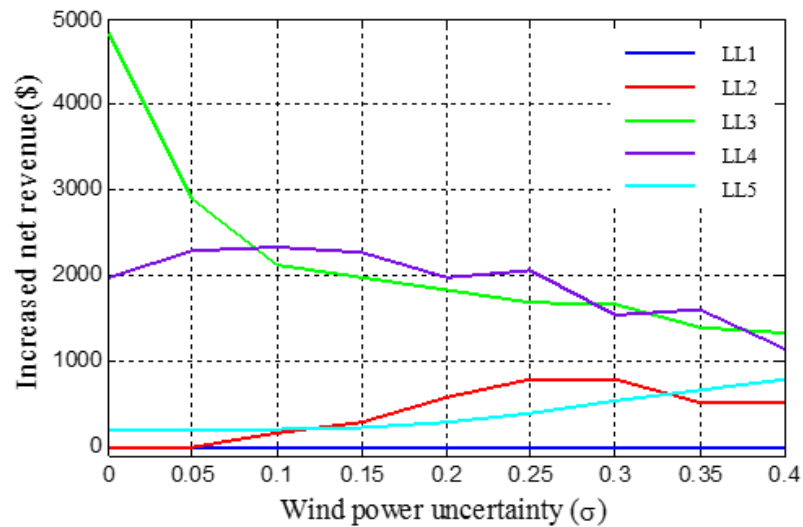


Figure 4.15 Impact of wind power forecast uncertainty on ENR on five typical operating points

In contrast, in LL2 and LL5, ΔENR has a moderate increasing trend when σ increases. The reason is that the LMP sensitivity in LL2 and LL5 rises when uncertainty increases. Consequently, a higher uncertainty may lead to a higher LMP and then greater values of ΔENR .

Further, when the operating point is extremely low, as in LL1, ΔENR may stay at zero because it is preferred to not active the CBDR program. This is aligned with the results in Case 1 in subsection V-B.

Thus, we can conclude that when the LMP at a specific load level is sensitive at that load level (e.g., LL3 and 4), ΔENR decreases with wind uncertainty; otherwise, ΔENR may increase with wind uncertainty.

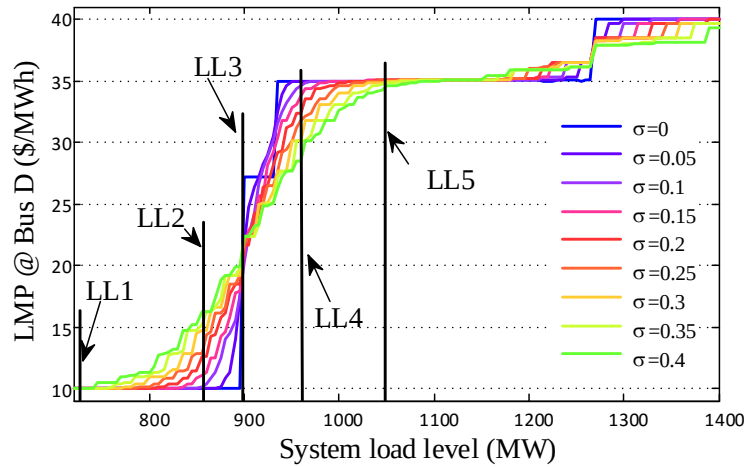


Figure 4.16 LMP against load level under various wind forecast uncertainty

4.5.5 IEEE 118-Bus System

The IEEE 118-bus system [55] is applied here to demonstrate applicability of the proposed method to larger systems. The system, as shown in Fig. 4.17, has 4242 MW load and 9966 MW generation capacity and consists of 118 buses, 54 generators and 186 branches.

The generator bidding data are similar with that in [3]: 20 low-cost generators with bids \$5, \$5.5 and from \$11 to \$19.5 with \$0.5 increment; 20 expensive generators with bids from \$30 to 49 with \$1 increment; and 14 most expensive generators with bidding from \$70 to 83 with \$1 increment. Seven thermal limits are applied to the transmission system: 100 MW for line 1-3 and 6-7, 175 MW for line 3-12 and 46-47, 150 MW for lines 15-33, 300 MW for line 71-72 and 250 MW for line 70-75.

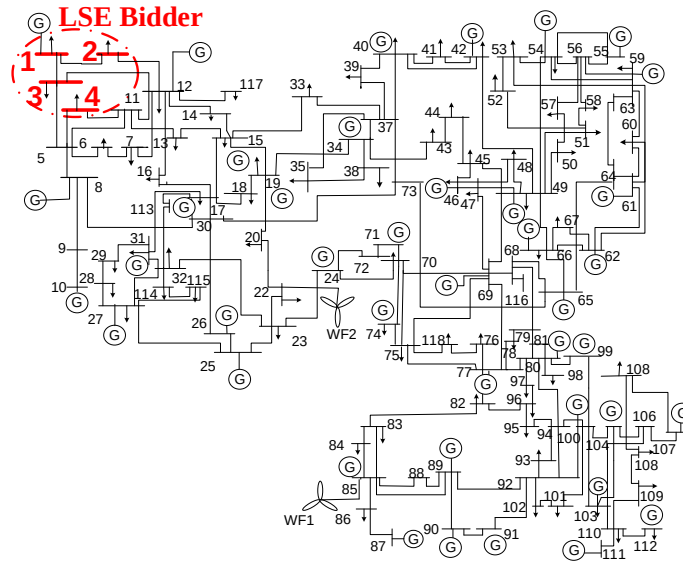


Figure 4.17 LSE bidder in IEEE 118-bus system integrated with two wind farms

Two wind power farms are connected at bus 85 (WF1) and bus 22 (WF2). At the bidding hour, the mean power from each wind farm is set as 300 MW with a 10% standard deviation (σ). The LSE performing the strategic bidding is located at the northwestern part of the system covering the demands on Bus 1, Bus 2, Bus 3 and Bus 4. LMPs on Bus 1 to Bus 4 versus the system load level is shown in Fig. 4.18. The coupon prices are set in the range between \$0/MWh and \$2.5/MWh with \$0.5/MWh as the increment step. Therefore, there are six different levels which are aligned with the six probabilistic levels of demand reduction from the survey data

obtained in [93], [94]. The demands at each bus of this LSE and the corresponding flat electricity rates are shown in Table 4.3. The load dispatched by the LSE for each bus and the ENR under different coupon price are in Table 4.4. Also, Table 4.5 shows the LSE's Bus LMPs.

The results in Table 4.4 shows that the LSE can obtain a considerable revenue increment from -\$237.882 to \$59.283 through CBDR with coupon price \$0.5 MW/h. However, the LSE's ENR decreases with the coupon price larger than \$0.5 MW/h. Two factors are related to this result:

Table 4.3 Load and Flat Electricity Rate on LSE Bidder's Buses

Bus	Base Load (MW)	Flat Electricity Rate (\$/MWh)
1	51	7.5
2	20	9.5
3	39	11.5
4	39	5.5

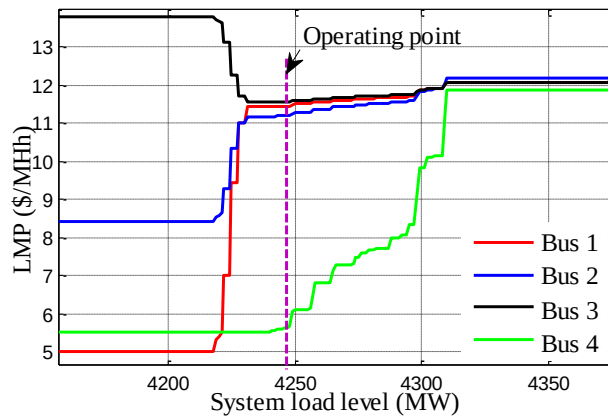


Figure 4.18 LMPs of LSE's buses in IEEE 118-bus system

Under this operation condition, a small demand reduction can cause the LMP drop to the lower level due to its step change pattern. Meanwhile, the change of LMP is not obvious with the further increasing the coupon price. As shown in Table 4.5, LMP on Bus 1 decreases from

\$11.441/MWh to \$5.000/MWh when the coupon price changes to \$0.5/MWh. Higher coupon price increases the payment from LSE to customers.

Moreover, it can be observed that the impacts of LSE's strategic behavior to the LMPs may vary at different buses. As demonstrated in Table 4.5, the LMP on Bus 3 increases while the LMPs on the other buses decrease. This observation is reasonable, because the objective of LSE is to maximize its total payoff gathered from all the customers on different buses. Therefore, it is possible that the LMP at a specific bus may increase with the LSE's strategic behavior, while the LSE's overall profit is maximized.

Table 4.4 Dispatched load on buses and LSE's ENR under different Coupon Prices

Coupon	Dispatched Load (MW)				ENR
	Bus 1	Bus 2	Bus 3	Bus 4	
0	51.000	20.000	39.000	39.000	-237.9
0.5	49.904	19.744	36.945	38.501	59.3
1.0	49.494	19.542	36.380	38.106	55.8
1.5	49.121	19.304	36.126	37.643	50.5
2.0	48.403	19.002	35.160	37.053	42.0
2.5	47.631	18.686	36.437	36.437	31.0

Table 4.5 LMP on buses under Different Coupon prices

Coupon	LMP (\$MW/h)			
	Bus 1	Bus 2	Bus 3	Bus
0	11.441	11.179	11.552	5.532
0.5	5.000	8.417	13.798	5.500
1.0	5.000	8.417	13.798	5.500
1.5	5.000	8.417	13.798	5.500
2.0	5.000	8.417	13.798	5.500
2.5	5.003	8.415	13.789	5.497

4.6 Conclusions

In this chapter, a strategic bidding approach for LSE with CBDR is proposed with the consideration of wind power uncertainty and customers' behavior patterns toward different coupon prices. The contributions of this work can be summarized as follows:

1. A strategic bidding model for LSEs using bi-level optimization for CBDR is proposed by recasting the lower-level problem into the KKT optimality condition. Thus, this bi-level problem is transformed to a MPEC problem, then further converted into a MILP problem which is easy to solve by available software tools.
2. A probabilistic model of residential demand is applied to mimic customers' behavior patterns toward different coupon prices. Therefore, the time-consuming interacting process with numerous customers can be avoided, which makes online implementation of CBDR feasible.
3. The strategic bidding is studied at five typical operating points representing different load levels. The simulation results demonstrate that change of expected net revenue (i.e., ΔENR) is closely related to the CLL, because this determines whether there will be a considerable price change or not if the load is reduced.
4. The wind power capacity does not change the patterns of ΔENR versus coupon prices, while the wind uncertainty may have an impact to ΔENR . ΔENR may either decrease with wind uncertainty when LMP is sensitive to load level or increase when LMP is not that sensitive to load level.

Furthermore, it should be noted that although the discussion in this chapter focuses on the strategic bidding in the RT market, similar mechanism or approach can be applied to the DA market as long as some price incentives are offered to encourage customers to participate in the

DA market such as TOU tariff, which can be roughly viewed as different CBDR at different time windows.

CHAPTER 5

IMPACTS OF FTR ON LSE STRATEGIC BIDDING CONSIDERING COUPON BASED DEMAND RESPONSE

5.1 Introduction

Financial transmission right (FTR) is a financial instrument that entitles the holders to receive compensation for transmission congestion charges arising when the transmission grid is congested in the day-ahead (DA) market and differences in DA congestion prices resulting from the dispatch of generators out of merit order (i.e., the ranking of available electrical generation based on ascending order of marginal cost) to relieve the congestion [110], [111]. Each FTR is defined from a point of receipt (where the power is injected on to the transmission grid) to a point of delivery (where the power is withdrawn from the transmission grid). For each hour in which congestion exists on the transmission system between the receipt and delivery points specified in the FTR, the holder of the FTR is awarded a share of the transmission congestion surplus collected from the market participants. The purpose of FTRs is to protect transmission service customers from increased cost due to transmission congestion when their energy deliveries are consistent with their FTR reservations [112].

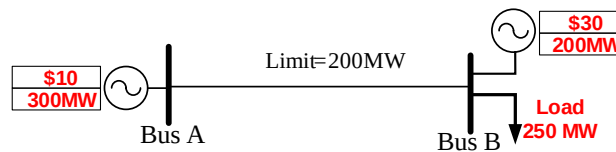


Figure 5.1 Illustration of congestion impact on the market clearing

Illustrated in Figure 5.1, when the load connected to Bus B exceeds the transmission limit from Bus A to Bus B, i.e., 200MW, congestion will occur. Thus, the locational marginal price (LMP) on Bus A and Bus B will be different which leads to the imbalance between generator revenue and load payment. Such imbalance is also called congestion surplus (CS), collected by Independent System Operators (ISOs). In this case, CS equals load payment ($\$30 \times 250 = \$7,500$) minus generator revenue ($\$10 \times 200 + \$30 \times 50 = \$3,500$), which is a total of \$4,000. If an LSE holds FTR from Bus A to Bus B with same amount of MW as the transmission limit, \$4,000 will be reimbursed to compensate for the over payment due to congestion. Therefore, FTR holdings of an LSE has big financial impact in its daily operations. An optimal bidding strategy of LSEs for any load portfolio (including demand response program) should almost always involve congestion analysis to be robust. Congestion pattern is tied up to many factors such as demand, outage etc. and is subjected to the uncertainties due to the renewable power output [36], [113], [114] and demand response program.

For the FTR optimization concerning the best paths and their MW amounts, there are several research literatures. In [112], the FTR portfolio optimization based on identification of congested network elements is proposed which overcomes the data handling and heaving computing burden of LMP difference based methods. In [115], a joint bidding model considering both FTR and energy market is proposed which is based on a two-tier matrix game approach. These papers focus on FTR portfolio optimization while demand response and wind power uncertainty are not considered. In this chapter, the impact of FTR on the LSE's bidding will be modeled in DA market instead of bidding FTR in the annual or monthly FTR auction.

DR programs in smart grids have been consistently gaining increasing popularity as alternative resources to help alleviate the grid pressure during peak load time [65] and improve

overall system operating efficiency and reliability. Achieving an optimal operation framework to dispatch DR resources has become a fast-growing interest in both industry and academia [81], [116]–[120]. While DR brings economic value to the system as a whole, it can also contribute to load serving entities' (LSEs) earnings. As LSEs continue to learn how to strategically utilize DR in the market to maximize the expected payoff in practice, most of the research works are focused on coordinating DR with the renewables [3], [121] and inducing consumers' inherent elasticity through DR program [122], [123]. In [122], an optimal bidding model for retailers is proposed considering the time-of-use demand response program and the market price uncertainties. In [123], the opportunity of demand response to reduce the potential wind curtailment in Ireland power system is analyzed.

In these previous studies, the viewpoints are mostly from system operators to dispatch DR resources for system optimal operation. Different from the aforementioned works, this chapter investigates coupon based demand response (CBDR) from the LSE's perspective. CBDR is similar to direct load control (DLC) program [81], [124], but customers have more flexibility in CBDR. Specifically, customers participate CBDR program voluntarily whereas the LSE directly controls the customer's appliances for DR events as long as the customer have a DLC contract with the LSE. As the survey stated in [77], DLC will have a promising potential through smart grid technologies in the future. Consequently, with more flexibility to the customers, CBDR will have a better implementation potential.

It is clear that CBDR program will change the demand level in certain area. Therefore, by performing CBDR, LSEs have the capability of altering congestion patterns which in turn leads to different earnings from their own FTR holdings. With both physical and financial instruments in hand, there is a growing need for LSEs to make sound decisions with the help of a framework

that can help investigate the coupling effects among various assets to achieve the maximization of its revenue or in another word, minimizing customers' cost through strategic participation in power market. The abovementioned papers focus on FTR portfolio optimization [112], [115] or DR optimization [3], [65], [81], [116]–[124] but fail to provide a comprehensive framework to analyze the optimal bidding strategy over an array of LSE's physical and financial assets under current market clearing methodology. This chapter proposes a comprehensive strategic bidding model that starts with FTR and CBDR and considers wind uncertainty as well. More specifically, an LSE offers a CBDR program to customers through the communication technique of smart grid and chooses the path of FTR for assessment. Next, the ISO's market-clearing procedure is implemented. Finally, the LSE can obtain the optimal bidding strategy with the maximum expected revenue including the congestion compensation from a specific FTR. The decision variables of LSE bidders are the optimal demand amount bids to the ISO and the corresponding coupon price offered to customers considering a specific FTR holding regarding the MW amount and path. Furthermore, the impact of different FTRs on LSE's strategic bidding regarding the FTR paths and amount can be analyzed based on the simulation results. To the knowledge of the authors, considering both physical measurement such as CBDR and financial instrument such as FTR in the strategic bidding has not been discussed in the previous literature.

The rest of this chapter is organized as follows: Section 2 presents the overall strategic bidding model for LSEs considering both FTR and CBDR. Section 3 presents the demand baseline model and the probabilistic demand reduction model under different coupon prices. Section 4 proposes the mathematic solution required to solve the stochastic bi-level model including the procedure of transforming it into a single level mathematic program with equilibrium constraints (MPEC) problem, and the conversion from MPEC to mixed-integer

linear programming (MILP) problem. Section 5 demonstrates the simulation results and numerical studies of an illustrative two bus system, PJM 5-bus system and IEEE 39-bus system to clearly verify the proposed method. Section 6 presents the summary and conclusion of this chapter.

5.2 Bidding Model for LSEs considering FTR and CBDR

5.2.1 Strategic Bidding in Deregulated Market

Figure 5.2(a) demonstrates the structure of a deregulated electricity market which includes both wholesale and retail market. Generation companies enter the wholesale market by offering their generating resources in the independent system operators (ISO)/regional transmission organizations (RTO) controlled area. Similarly, LSEs provide their demand bids which are to be cleared together with all the generation bids. After ISO/RTO clears the market by performing least cost unit commitment (UC) and economic dispatch (ED), the generation company will receive revenue once their resources are picked up in the corresponding market and LSEs will pay for the electricity procurement for their cleared energy bids.

The illustration of LSEs' strategic bidding under this market structure will be discussed in the following subsections 2.2 to 2.4. The congestion compensation from FTR can be obtained from DA market when the transmission lines are congested. Therefore, in this chapter, the strategic bidding is performed in DA market.

5.2.2 Revenue of LSEs considering FTR and CBDR

There are two contributors to an LSE's revenue in the framework shown in Figure 5.2(b), i.e., 1) retail sales from each customer k ($k \in B_i$) at bus i ($i \in A$), as shown in k_4 to k_7 of LSE A and 2) FTR revenue if the upstream transmission network has seen congestions. The revenue from 1) is calculated as the product of the retail price $\eta_{i,k}$ and the electricity consumption $D_{i,k}$ minus the

cost of serving load includes payment to ISO from purchasing power in the wholesale market (i.e., the product of spot price π_i and the electricity consumption $D_{i,k}$) as well as the financial incentives paid to customers to schedule DR resources (i.e., the product of coupon price $r_{i,k}$ and the demand reduction from the baseline electricity consumption to the actual electricity demand). The revenue from 2) is derived from the product of LMP difference between the injection bus and delivery bus, and the MW amount of FTR. Thus, the LSE's net revenue is expressed as (1):

$$\sum_{i \in A} \left(\sum_{k \in B_i} (\eta_{i,k} \times D_{i,k} - r_{i,k} \times (D_{i,k}^0 - D_{i,k})) - \pi_i \times D_i \right) + \sum_{\{ij \in \Gamma\}} [\Delta \pi_{ij} \cdot FTR_{ij}] \quad (5.1)$$

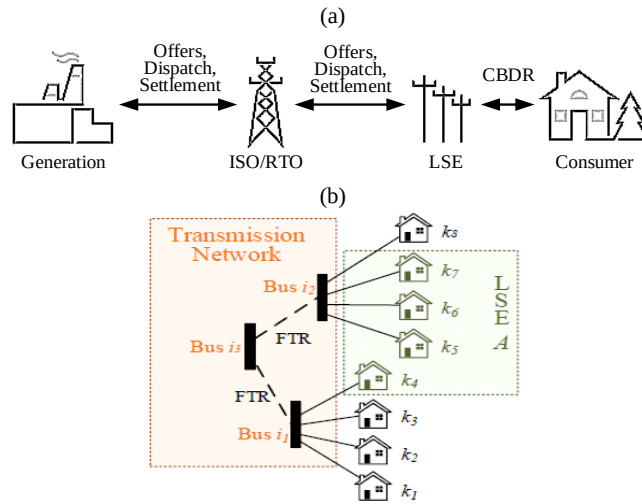


Figure 5.2 Structure of the electricity market

The decision variables are the optimal demand bids $D_{i,k}$ and optimal coupon price $r_{i,k}$. It should be noted that the LMP π_i and the LMP difference $\Delta \pi_{ij}$ in (5.1) is obtained from the ISO's ED [18], which will be discussed in subsection 2.3.

5.2.3 ISO's Market Clearing

There are different operational rules in different markets, but they share the same critical element in the market clearing process, i.e., a security constrained unit commitment (SCUC) [125] to bring the most economic units online and a security constrained economic dispatch (SCED) to determine the optimal schedule from each generating units. As the CBDR program is between LSEs and customers, the demands in the ISOs' ED model are assumed to hold no elasticity. A lossless DC optimal power flow (DCOPF) model with fixed transmission network is assumed, and generations are considered fully competitive and rational in bidding at their marginal costs [91], [92], which is aligned with various DCOPF models utilized by many ISOs [90]. Thus, the DCOPF approach is employed here to model the electricity market clearing process and simulate LMPs. The decision variable in this level is the optimal generation dispatch G_i . The DCOPF is essentially a linear programming (LP) problem as:

$$\min \sum_{i=1}^N c_i \times G_i \quad (5.2a)$$

$$\text{s.t. } \sum_{i=1}^N G_i = \sum_{i=1}^N D_i : \lambda \quad (5.2b)$$

$$D_i = \sum_{k \in B_i} D_{i,k}, \forall i \in A \quad (5.2c)$$

$$-Limit_l \leq \sum_{i=1}^N GSF_{l-i} \times (G_i - D_i) \leq Limit_l : \mu_l^{\min}, \mu_l^{\max}, \forall l = 1, 2, \dots, M \quad (5.2d)$$

$$G_i^{\min} \leq G_i \leq G_i^{\max} : \omega_i^{\min}, \omega_i^{\max}, \forall i = 1, 2, \dots, N \quad (5.2e)$$

The LMP can be calculated with the Lagrangian function of the above ED optimization model. This function and LMP can be written as:

$$\begin{aligned} \psi = & \left(\sum_{i=1}^N c_i \times G_i \right) - \lambda \left(\sum_{i=1}^N G_i - \sum_{i=1}^N D_i \right) - \sum_{l=1}^M \mu_l^{\min} \left(\sum_{i=1}^N GSF_{l-i} \times (G_i - D_i) + Limit_l \right) \\ & - \sum_{l=1}^M \mu_l^{\max} \left(Limit_l - \sum_{i=1}^N GSF_{l-i} \times (G_i - D_i) \right) - \sum_{i=1}^N \omega_i^{\min} (G_i - G_i^{\min}) - \sum_{i=1}^N \omega_i^{\max} (G_i^{\max} - G_i) \end{aligned} \quad (5.2f)$$

$$\pi_i = \frac{\partial \psi}{\partial D_i} = \lambda + \sum_{l=1}^M GSF_{l-i} (\mu_l^{\min} - \mu_l^{\max}) \quad (5.2g)$$

From the expression of LMP in (5.2g), the LMP difference $\Delta\pi_{ij}$ between bus i and bus j can be derived as:

$$\Delta\pi_{ij} = \sum_{l=1}^M (GSF_{l-i} - GSF_{l-j}) \cdot (\mu_l^{\min} - \mu_l^{\max}) \quad (5.2h)$$

5.2.4 Bi-level Model of LSE's Strategic Bidding

LSE's bidding process considering CBDR and FTR is essentially a bi-level optimization problem, where the decision variables (demand bids and coupon prices) affect not only the LSE's own condition and constraints but also the ISO's clearing result. In addition, different levels of demand reduction will lead to different congestion pattern and FTR earnings. Assuming the capacity of CBDR resources have enough market impact, the dynamics between market clearing price, both LMP and MCC (Marginal Congestion Component) is well worth studied. Therefore, the bi-level strategic bidding problem is formulated as follows in (5.3a)-(5.3c). The upper level is to maximize the LSE's profit, and the lower level is to minimize the generation cost to model the ISO's market-clearing process [92], [126], [127]:

$$\begin{aligned} \text{Max} \quad & \sum_{i \in A} \left(\sum_{k \in B_i} (\eta_{i,k} \times D_{i,k} - r_{i,k} \times (D_{i,k}^0 - D_{i,k})) - \pi_i \times D_i \right) \\ & + \sum_{\{ij \in \Gamma\}} \left[\sum_{l=1}^M (GSF_{l-i} - GSF_{l-j}) \cdot (\mu_l^{\min} - \mu_l^{\max}) \cdot FTR_{ij} \right] \end{aligned} \quad (5.3a)$$

$$\text{s.t.} \quad D_{i,k}^{\min} \leq D_{i,k} \leq D_{i,k}^{\max}, \forall i \in A, k \in B_i \quad (5.3b)$$

$$\text{where } \pi_i, \forall i \in \arg\{(2a) - (2e), (2g), (2h)\} \quad (3c)$$

where $D_{i,k}^{\min}$ and $D_{i,k}^{\max}$ are the minimum and maximum demand values of demand k at bus i respectively. The LMP π_i and the difference $\Delta\pi_{ij}$ among the injection and delivery buses of FTR from the ED depends on the demand, $D_{i,k}$, as well as the bid prices/quantities of generators.

The demand baseline D^0 , and potential demand reduction block $D_{i,k}^{\min}$ and $D_{i,k}^{\max}$ are covered in Section 3. Then, the mathematic algorithm to solve (5.3a)-(5.3c) will be presented in Section 4.

5.3 Baseline Demand and Probabilistic Demand Reduction

5.3.1 Baseline Demand Model

The CBDR programs are critically dependent on the customers' demand baseline [93] from which the demand reduction in DR can be calculated. Due to the strong cyclic pattern of customers' electricity consumption over time [94], the demand baseline can be forecast with historical data. For instance, Southern California Edison (SCE) employs an approach called "10-Day Average Baseline" [95]. More details concerning the baseline calculation have been introduced in [96], though it is out of the research scope of this chapter to discuss the pros and cons of various consumer demand baseline methods.

5.3.2 Probabilistic Demand Reduction Model

This chapter adopts a practical and validated probabilistic model of potential demand reduction under different coupon prices, which has been introduced in [128]. This model is able to directly assess the probability distribution of residential demand reduction to certain coupon price for a given time, location and customers' portfolios as shown in Figure 5.3(a).

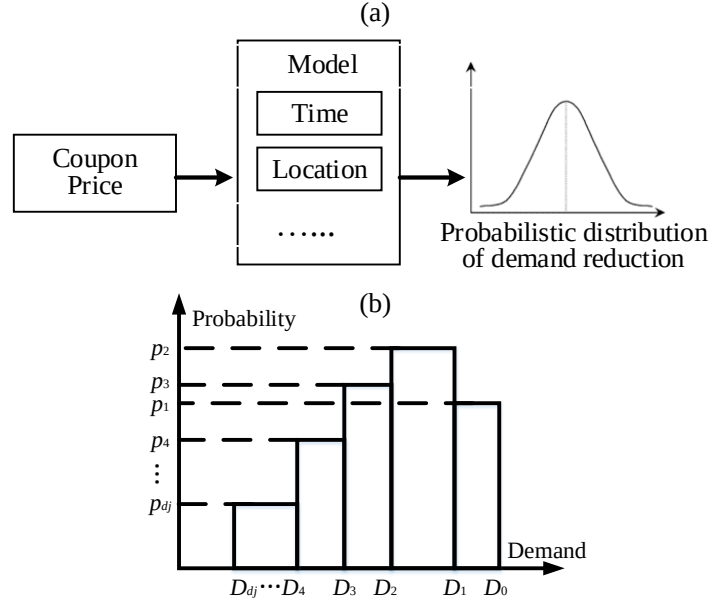


Figure 5.3 Schematic of the demand reduction model and probabilistic demand reduction

With this probabilistic demand reduction model, under the j^{th} coupon, the probabilistic demand blocks are $[D_{j,1}, D_{j,2}]$, $[D_{j,2}, D_{j,3}]$, ..., $[D_{j,d}, D_{j,d}]$, ..., $[D_{j,dj}, D_{j,dj}]$ with a probability set of $\{p_d\}$ as shown in Figure 3(b) where dj is the total number of demand block under the j^{th} coupon price.

5.4 Mathematical Solution of the Proposed Model

As introduced in Section 2, the strategic bidding problem in (5.3a) to (5.3c) is formulated as a bi-level optimization problem with a coupling effect due to the existence of dependent variables in each level. More specifically, the LMP in the upper level is determined by the lower level ISO's market clearing, while the demands at load buses of LSE bidders in the lower level depend on the upper level's demand. In this chapter, DCOPF is implemented to clear the ISO's market.

5.4.1 Formulation of Single Level Optimization Model

The bi-level strategic bidding model can be transformed to a single level MPEC by recasting the lower level problem as its KKT optimality conditions due to the linearity of lower level ED problem [92], [101], [129], and then adding these conditions into the upper level as a set of additional complementarity constraints [103], [130]. Therefore, the bi-level strategic bidding model (5.3a)-(5.3c) is transformed as a MPEC problem in (5.4a)-(5.4g):

$$\begin{aligned} & \sum_{i \in A} \left(\sum_{k \in B_i} (\eta_{i,k} \times D_{i,k} - r_{i,k} \times (D_{i,k}^0 - D_{i,k})) - \pi_i \times D_i \right) \\ \text{Max} & + \sum_{\{ij \in \Gamma\}} \left[\sum_{l=1}^M (GSF_{l-i} - GSF_{l-j}) \cdot (\mu_l^{\min} - \mu_l^{\max}) \cdot FTR_{ij} \right] \end{aligned} \quad (5.4a)$$

$$\text{s.t. Constraint in (5.2b), (5.2c), (5.2g), (5.2h) and (5.3b)} \quad (5.4b)$$

$$c_i = \lambda + \sum_{l=1}^M GSF_{l-i} \times (\mu_l^{\min} - \mu_l^{\max}) + \omega_i^{\min} - \omega_i^{\max} \quad (5.4c)$$

$$0 \leq \mu_i^{\min} \perp \text{Limit}_i + \sum_{i=1}^N GSF_{l-i} \times (G_i - D_i) \geq 0 \quad (5.4d)$$

$$0 \leq \mu_i^{\max} \perp \text{Limit}_i - \sum_{i=1}^N GSF_{l-i} \times (G_i - D_i) \geq 0 \quad (5.4e)$$

$$0 \leq \omega_i^{\min} \perp G_i - G_i^{\min} \geq 0 \quad (4f)$$

$$0 \leq \omega_i^{\max} \perp G_i^{\max} - G_i \geq 0 \quad (4g)$$

where (5.4c)-(5.4g) are the ED problem's KKT optimality conditions; the perpendicular sign $\perp$ denotes a zero cross product of the corresponding variables in vector form.

5.4.2 Congestion Surplus

As introduced previously, when the transmission system is congested in ISO's market clearing, the congestion surplus (CS) exists. This surplus is the deviation between the revenue collected from all the consumers and the payment to all the generation which can be expressed as

$$CS = \sum_{i=1}^N \pi_i \cdot (D_i - G_i) \quad (5.5)$$

The transformation of CS is given below:

From (5.2g) and (5.4c), LMP can be expressed as:

$$\pi_i = c_i + \omega_i^{\max} - \omega_i^{\min} \quad (5.6)$$

With the KKT conditions (5.4f), we have

$$\omega_i^{\min} \cdot (G_i - G_i^{\min}) = 0 \quad (5.7)$$

$$\text{and } \omega_i^{\min} \cdot G_i = \omega_i^{\min} \cdot G_i^{\min}$$

Similarly, with (5.4g), it can be derived that

$$\omega_i^{\max} \cdot G_i^{\max} = \omega_i^{\max} \cdot G_i \quad (5.8)$$

Therefore,

$$\sum_{i=1}^N \pi_i \cdot G_i = \sum_{i=1}^N (c_i \cdot G_i + \omega_i^{\max} \cdot G_i^{\max} - \omega_i^{\min} \cdot G_i^{\min}) \quad (5.9)$$

According to the strong duality theory, the objective of the primal problem is equal to the objective of the corresponding dual problem. For the ED problem, the relationship between the objectives of the dual and primal problems can be expressed as follows:

$$\begin{aligned}
& \lambda \times \sum_{i=1}^N D_i + \sum_{l=1}^M \mu_l^{\max} \times (-Limit_l - \sum_{i=1}^N GSF_{l-i} \times D_i) + \sum_{l=1}^M \mu_l^{\min} \times (-Limit_l + \sum_{i=1}^N GSF_{l-i} \times D_i) \\
& + \sum_{i=1}^N \omega_i^{\max} \times (-G_i^{\max}) + \sum_{i=1}^N \omega_i^{\min} \times (G_i^{\min}) = \sum_{i=1}^N c_i \times G_i
\end{aligned} \tag{5.10}$$

From the LMP expression in (5.2g), the product term $\pi_i \times D_i$ can be transformed as (5.11) below.

$$\sum_{i=1}^N \pi_i \times D_i = \sum_{i=1}^N \left[\lambda \times D_i + \sum_{l=1}^M GSF_{l-i} (\mu_l^{\min} - \mu_l^{\max}) \times D_i \right] \tag{5.11}$$

Taking (5.10) into (5.11),

$$\begin{aligned}
\sum_{i=1}^N \pi_i \times D_i &= \sum_{i=1}^N c_i \times G_i - \sum_{l=1}^M \mu_l^{\max} \times (-Limit_l) - \sum_{l=1}^M \mu_l^{\min} \times (-Limit_l) \\
&\quad - \sum_{i=1}^N \omega_i^{\max} \times (-G_i^{\max}) - \sum_{i=1}^N \omega_i^{\min} \times (G_i^{\min})
\end{aligned} \tag{5.12}$$

Finally, considering (5.9) and (5.12), we have congestion surplus expressed as:

$$\begin{aligned}
& \sum_{i=1}^N \pi_i \times D_i - \sum_{i=1}^N \pi_i \cdot G_i \\
&= \sum_{i=1}^N c_i \times G_i - \sum_{l=1}^M \mu_l^{\max} \times (-Limit_l) - \sum_{l=1}^M \mu_l^{\min} \times (-Limit_l) \\
&\quad - \sum_{i=1}^N \omega_i^{\max} \times (-G_i^{\max}) - \sum_{i=1}^N \omega_i^{\min} \times (G_i^{\min}) - \sum_{i=1}^N (c_i \cdot G_i + \omega_i^{\max} \cdot G_i^{\max} - \omega_i^{\min} \cdot G_i^{\min}) \\
&= \sum_{l=1}^M (\mu_l^{\max} + \mu_l^{\min}) \times (Limit_l)
\end{aligned} \tag{5.13}$$

5.4.3 Mixed-integer Linear Programming (MILP) with FTR and CBDR

The objective function (the product term $\pi_i \times D_{i,k}$) and the complementarity constraints (5.4d)-(5.4g) leads the nonlinearity of the MPEC model (5.4a)-(5.4g). First, through the strong duality theory, the objective function can be linearized [103]–[105]. Then with the method proposed in [64], the constraints (5.4d)-(5.4g) are transformed in a set of linear constraints.

Therefore, the objective in (5.4a) considering FTR and CBDR can be expressed as

(5.14a) and the MPEC problem is converted as a MILP problem as:

$$\begin{aligned}
\max & \sum_{i \in A} \sum_{k \in B_i} (\eta_{i,k} \times D_{i,k} - r_{i,k} \times (D_{i,k}^0 - D_{i,k})) - \sum_{i=1}^N c_i \times G_i \\
& + \lambda \times \sum_{i \notin A} D_i + \sum_{l=1}^M \mu_l^{\max} \times (-Limit_l - \sum_{i \notin A} GSF_{l-i} \times D_i) \\
& + \sum_{l=1}^M \mu_l^{\min} \times (-Limit_l + \sum_{i \notin A} GSF_{l-i} \times D_i) \\
& + \sum_{i=1}^N \omega_i^{\max} \times (-G_i^{\max}) + \sum_{i=1}^N \omega_i^{\min} \times (G_i^{\min}) \\
& + \sum_{\{ij \in \Gamma\}} \left[\sum_{l=1}^M (GSF_{l-i} - GSF_{l-j}) \cdot (\mu_l^{\min} - \mu_l^{\max}) \cdot FTR_{ij} \right]
\end{aligned} \tag{5.14a}$$

$$\text{s.t. Constraints in (5.4b) and (5.4c)} \tag{5.14b}$$

$$0 \leq \mu_l^{\min} \leq M_{\mu}^{\min} \nu_{\mu,l}^{\min} \tag{5.14c}$$

$$0 \leq Limit_l + \sum_{i=1}^N GSF_{l-i} \times (G_i - D_i) \leq M_{\mu}^{\min} (1 - \nu_{\mu,l}^{\min}) \tag{5.14d}$$

$$0 \leq \mu_l^{\max} \leq M_{\mu}^{\max} \nu_{\mu,l}^{\max} \tag{5.14e}$$

$$0 \leq Limit_l - \sum_{i=1}^N GSF_{l-i} \times (G_i - D_i) \leq M_{\mu}^{\max} (1 - \nu_{\mu,l}^{\max}) \tag{5.14f}$$

$$0 \leq \omega_i^{\min} \leq M_{\omega}^{\min} \nu_{\omega,i}^{\min} \tag{5.14g}$$

$$0 \leq G_i - G_i^{\min} \leq M_{\omega}^{\min} (1 - \nu_{\omega,i}^{\min}) \tag{5.14h}$$

$$0 \leq \omega_i^{\max} \leq M_{\omega}^{\max} \nu_{\omega,i}^{\max} \tag{5.14i}$$

$$0 \leq G_i^{\max} - G_i \leq M_{\omega}^{\max} (1 - \nu_{\omega,i}^{\max}) \tag{5.14j}$$

where $M_{\mu}^{\min}$, $M_{\mu}^{\max}$, $M_{\omega}^{\min}$, and $M_{\omega}^{\max}$ are large enough constants, and $\nu_{\mu,l}^{\min}$, $\nu_{\mu,l}^{\max}$, $\nu_{\omega,i}^{\min}$, and $\nu_{\omega,i}^{\max}$ are the auxiliary binary variables [49].

5.4.4 Integrating Uncertainty of Wind Power and CBRD

In this subsection, the extensions of the above model, including the uncertainty of wind power and demand reduction under a certain coupon price, will be discussed. The forecasted wind power production is expressed as a set of probabilistic scenarios ($s = 1 \sim S$) with a probability set of $\{p_s\}$. And assume that under the j^{th} coupon, the probabilistic demand blocks are $[D_{j,1}, D_{j,2}], [D_{j,2}, D_{j,3}], \dots, [D_{j,d}, D_{j,d}], \dots, [D_{j,dj}, D_{j,dj}]$ with a probability set of $\{p_d\}$, where dj is the total number of demand block under the j^{th} coupon price. The model below in (5.15a)-(5.15e) is an example of an ED model that includes one scenario of wind power and demand reduction.

$$\min \sum_{i=1}^N c_i \times G_i^{j,d,s} \quad (5.15a)$$

$$\text{s.t.} \sum_{i=1}^N (G_i^{j,d,s} + P_{W,i}^s) = \sum_{i=1}^N D_{i,j,d} : \lambda^{j,d,s} \quad (5.15b)$$

$$D_{i,j,d} = \sum_{k \in B_i} D_{i,k,j,d}, \forall i \in A \quad (5.15c)$$

$$-Limit_l \leq \sum_{i=1}^N GSF_{l-i} \times (G_i^{j,d,s} + P_{W,i}^s - D_{i,j,d}) \leq Limit_l : \mu_l^{j,d,s,\min}, \mu_l^{j,d,s,\max}, \forall l = 1, 2, \dots, M \quad (5.15d)$$

$$G_i^{\min} \leq G_i^{j,d,s} \leq G_i^{\max} : \omega_i^{j,d,s,\min}, \omega_i^{j,d,s,\max}, \forall i = 1, 2, \dots, N \quad (5.15e)$$

where $G_i^{j,d,s}$ is the generation dispatch at bus i (MWh) under the d^{th} demand block of the j^{th} coupon price and the s^{th} wind scenario.

The LMP is given by

$$\pi_i^{j,d,s} = \lambda^{j,d,s} + \sum_{l=1}^M GSF_{l-i} (\mu_l^{j,d,s,\min} - \mu_l^{j,d,s,\max}) \quad (5.15f)$$

Therefore, the net revenue of LSE can be formulated as (5.16a) and then transformed to (5.16b), and the constraints are modeled in (5.16c) to (5.16m).

$$\begin{aligned} \max \sum_{d=1}^{dj} p_{j,d} \times & \left\{ \sum_{i \in A} \left(\sum_{k \in B_i} (\eta_{i,k} \times D_{i,k,j,d} - r_{i,k,j} \times (D_{i,k}^0 - D_{i,k,j,d})) \right) \right\} \\ & - \sum_{s=1}^S p_s \times \left(\pi_i^{j,d,s} \times D_{i,j,d} - \sum_{\{ij \in \Gamma\}} (\Delta \pi_{ij}^{j,d,s} \cdot FTR_{ij}) \right) \end{aligned} \quad (5.16a)$$

$$\begin{aligned} \max \sum_{d=1}^{dj} p_{j,d} \times & \left\{ \sum_{i \in A} \left(\sum_{k \in B_i} (\eta_{i,k} \times D_{i,k,j,d} - r_{i,k,j} \times (D_{i,k}^0 - D_{i,k,j,d})) \right) \right\} \\ & - \sum_{s=1}^S p_s \times \left\{ \sum_{i=1}^N c_i \times G_i^{j,d,s} - \lambda^{j,d,s} \times \left(\sum_{i \notin A} D_i - \sum_{i=1}^N P_{W,i}^s \right) \right. \\ & - \sum_{l=1}^M \mu_l^{j,d,s,\max} \times [-Limit_l + \sum_{i=1}^N GSF_{l-i} \times P_{W,i}^s \\ & - \sum_{i \notin A} GSF_{l-i} \times D_i] - \sum_{l=1}^M \mu_l^{j,d,s,\min} \times [-Limit_l \\ & - \sum_{i=1}^N GSF_{l-i} \times P_{W,i}^s + \sum_{i \notin A} GSF_{l-i} \times D_i] \\ & - \sum_{i=1}^N \omega_i^{j,d,s,\max} \times (-G_i^{\max}) - \sum_{i=1}^N \omega_i^{j,d,s,\min} \times (G_i^{\min}) \\ & \left. - \sum_{\{ij \in \Gamma\}} \left[\sum_{l=1}^M (GSF_{l-i} - GSF_{l-j}) \cdot (\mu_l^{j,d,s,\min} - \mu_l^{j,d,s,\max}) \cdot FTR_{ij} \right] \right\} \end{aligned} \quad (5.16b)$$

$$\text{s.t. Constraints (5.14b) and (5.14c)} \quad (5.16c)$$

$$D_{i,k,j,d}^{\min} \leq D_{i,k,j,d} \leq D_{i,k,j,d}^{\max}, \forall i \in A, k \in B_i \quad (5.16d)$$

$$c_i = \lambda^{j,d,s} + \sum_{l=1}^M GSF_{l-i} \times (\mu_l^{j,d,s,\min} - \mu_l^{j,d,s,\max}) + \omega_i^{j,d,s,\min} - \omega_i^{j,d,s,\max} \quad (5.16e)$$

$$0 \leq \mu_l^{j,d,s,\min} \leq M_{\mu}^{\min} \nu_{\mu,l}^{j,d,s,\min} \quad (5.16f)$$

$$0 \leq Limit_l + \sum_{i=1}^N GSF_{l-i} \times (G_i^{j,d,s} + P_{W,i}^s - D_{i,j,d}) \leq M_{\mu}^{\min} (1 - \nu_{\mu,l}^{j,d,s,\min}) \quad (5.16g)$$

$$0 \leq \mu_l^{j,d,s,\max} \leq M_\mu^{\max} \nu_{\mu,l}^{j,d,s,\max} \quad (5.16h)$$

$$0 \leq \text{Limit}_l - \sum_{i=1}^N \text{GSF}_{l-i} \times (G_i^{j,d,s} + P_{W,i}^s - D_{i,j,d}) \leq M_\mu^{\max} (1 - \nu_{\mu,l}^{j,d,s,\max}) \quad (5.16i)$$

$$0 \leq \omega_i^{j,d,s,\min} \leq M_\omega^{\min} \nu_{\omega,i}^{j,d,s,\min} \quad (5.16j)$$

$$0 \leq G_i^{j,d,s} - G_i^{\min} \leq M_\omega^{\min} (1 - \nu_{\omega,i}^{j,d,s,\min}) \quad (5.16k)$$

$$0 \leq \omega_i^{j,d,s,\max} \leq M_\omega^{\max} \nu_{\omega,i}^{j,d,s,\max} \quad (5.16l)$$

$$0 \leq G_i^{\max} - G_i^{j,d,s} \leq M_\omega^{\max} (1 - \nu_{\omega,i}^{j,d,s,\max}) \quad (5.16m)$$

where the model above in (5.16b)-(5.16m) gives the optimal profit under a certain coupon price. When the profits under different coupon prices are obtained, the LSE can choose the optimal coupon price with the maximum profit and the corresponding demand dispatch to bid in ISO's market. Note that the uncertainty of other LSEs' demand bids as well as the generation prices can be included in the model as an additional set of scenarios.

5.5 Case Studies

In this section, the proposed strategic bidding approach considering both CBDR and FTR is performed on three systems. The investigation of the first simple system (two buses, two generators and one load) is aimed to validate our methodology. The rest case studies on a modified PJM 5-bus system [92] and IEEE 39-bus system further verify the proposed method. The MILP problem is solved with GAMS [54].

5.5.1 Illustrative Two-bus system

The two-bus system depicted in Figure 5.1 is utilized to illustrate the impact of FTR on LSE's bidding. The system parameters such as generators' capacities, bid prices, transmission line limits and loads are shown in Figure 5.1. The flat rate that the LSE offers to customers is \$25/MWh. Three cases are investigated to demonstrate the impact of CBDR and FTR on the LSE's bidding, respectively.

Case 1: without CBDR and FTR;

Case 2: with CBDR but without FTR;

Case 3: with both CBDR and FTR.

In the CBDR, the coupon price is set to be \$10/MWh and 25% of load is responsive to this coupon price. The FTR amount from Bus A to B is 200 MW. The results in three cases are listed in Table 5.1 and Eq. 5.17 and 5.18 illustrate the LSE's net revenue in Case 2 and Case 3 under different load level.

$$R = \begin{cases} 25 \times D - 30 \times D - 10 \times (250 - D), & 200 \leq D \leq 250 \\ 25 \times D - 10 \times D - 10 \times (250 - D), & D < 200 \end{cases} \quad (5.17)$$

$$R = \begin{cases} 25 \times D - 30 \times D - 10 \times (250 - D) + 200 \times 20, & 200 \leq D \leq 250 \\ 25 \times D - 10 \times D - 10 \times (250 - D), & D < 200 \end{cases} \quad (5.18)$$

Table 5.1 Bidding results in three cases

Cases	Opt. Load (MW)	Profit (\$)	LMP at Bus A (\$/MWh)	LMP at Bus B (\$/MWh)
Case 1	250.00	-1250.00	10	30
Case 2	199.99	2499.75	10	10
Case 3	250.00	2750.00	10	30

The results in Table 5.1 shows that the LSE will have a negative profit (-\$1250) if it does not perform CBDR and does not hold the FTR from Bus A to Bus B. In other words, the LSE on Bus B loses money at this operating point. In Case 2, from Eq. 5.17, the LSE will reduce its load to decrease the LMP at Bus B. In this case, the optimal load level is infinitely close to but lower than 200 MW. Because if its load is lower than 200 MW, the LMP at Bus B is \$10/MWh which equals the bid price of the generator at Bus A. However, if the load is equal to or higher than 200 MW, the LMP at Bus B will increase to \$30/MWh. When LMP at Bus B is \$10/MWh lower than the flat rate of \$25/MWh, the LSE is profitable under this LMP level. Therefore, it will increase the load to its highest level while maintains this lower LMP of \$10/MWh at Bus B unchanged. Consequently, the optimal load at Bus B should be close to but lower than 200 MW.

In Case 3, from Eq. 5.18, the LSE holds a 200 MW FTR from Bus A to B. Since the LMP at Bus B is \$30/MWh, higher than the flat rate, the LSE will make a negative profit from selling electricity to customers. However, it obtains more profit from the FTR's congestion compensation which is $(30-10) \times 200$. Therefore, in this case, after considering the benefit from FTR's congestion compensation, the LSE has no incentive to perform CBDR to reduce its load. This is a simple case to illustrate the impact of FTR on LSE's bidding and the simulation performed on the complex system will be presented in the following subsections.

5.5.2 PJM 5-Bus Test System

The test system is modified from the PJM 5-bus system depicted in Figure 5.4. The system parameters are from [92]. The forecast power output of two wind power plants (WF1 and WF2) are 180 MW under a normal distribution with 18MW as its standard deviation [109]) added into the system at buses A and C, while one of the two original generators at bus A is removed. The total load is equally distributed between buses B, C, and D.

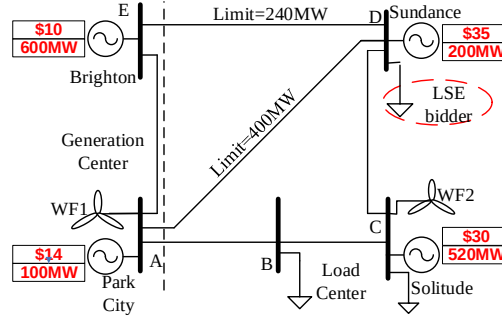


Figure 5.4 PJM 5-bus system with two wind farms

In the case study, the LSE bidder is located at Bus D. The flat electricity rate offered to the customers at Bus D is set to \$20/MWh. Also, this study assumes the coupon price is between \$0/MWh and \$10/MWh with \$1 as the incremental step such that there are 11 different coupon prices aligned with 11 probabilistic distribution of demand reduction generated by the demand reduction model in Section 3.

The impact of FTR on the strategic bidding is investigated on different FTR paths and amounts. The base load level is 300 MW on all three load buses. Figure 5.5(a) to Figure 5.5(d) are the LSE's expected net revenue with various paths and amounts of FTRs under different coupon prices. Figure 5.5(a) to Figure 5.5(d), specify the FTR paths from Bus A to Bus D, Bus B to Bus D, Bus C to Bus D, and Bus E to Bus D, respectively. The green lines on the figures identify the optimal coupon prices under the specific FTR path and MW amount, which cause the LSE to obtain the highest revenue. These figures show that the impact of FTR on the strategic bidding varies w.r.t. FTR paths and amounts.

Figure 5.6 is the buses' expected LMPs under different coupon prices when the LSE on Bus D does not hold FTR. This figure demonstrates that the LMPs, except Bus E, decrease with the coupon price. Because, with the increasing coupon price, the load on LSE's bus decreases which leads to a reduction of the bus LMPs. Also, it can be observed that the LMP difference

between Bus D and other buses decreases w.r.t. coupon price. This means that the congestion benefit from the LSE's FTR holding from other buses to Bus D will decrease with the increasing coupon price. Therefore, in the LSE's strategic bidding considering both CBDR and FTR, it should consider the benefit from FTR through maintaining high load level to obtain the congestion compensation and the benefit from selling electricity to customers with a lower LMP cost. With the method proposed in this chapter, the global optimal strategic bidding decision can be obtained.

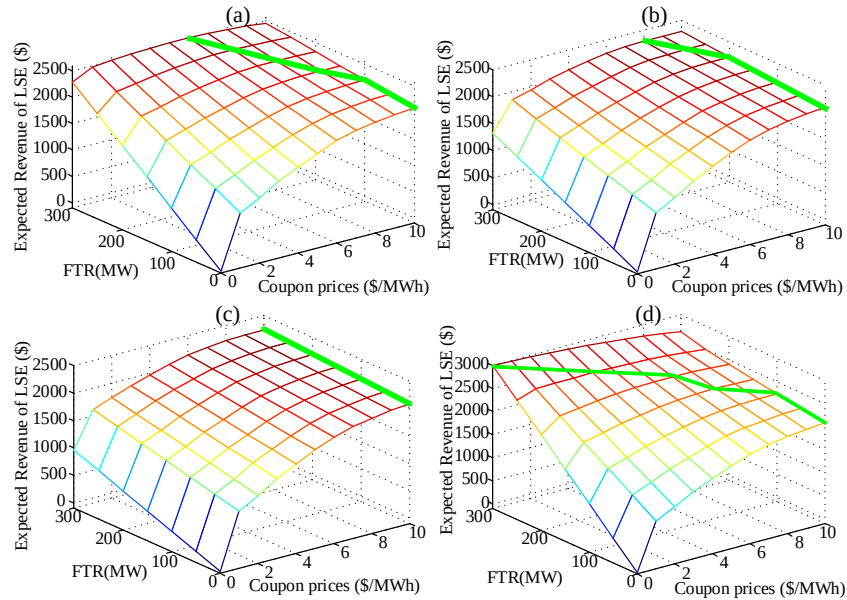


Figure 5.5 Expected revenue under different coupon prices and different FTRs

Table 5.2 lists the optimal demand level and coupon prices with which the LSE can obtain the maximum profit with 300 MW FTR on different paths. It shows that with this FTR amount, when the path is from Bus E to D, the LSE has no incentive to offer coupons to customers. While on the path from Bus C to D, the FTR does not change the bidding results regarding the demand amount and coupon price. But, the LSE can still obtain more profit through congestion compensation. The maximum profit that the LSE can obtain with CBDR and

FTR decreases with the LMP differences between the injection buses and delivery buses of different FTR paths.

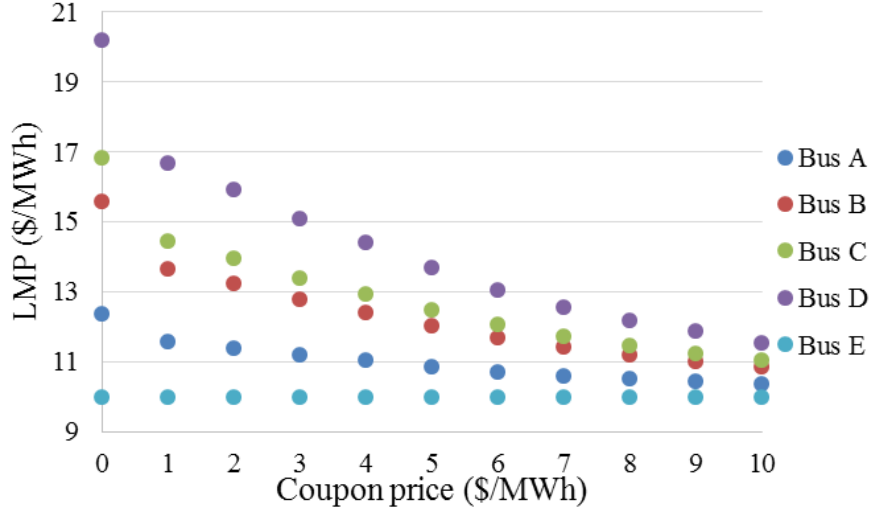


Figure 5.6 Bus LMPs with different coupon prices

Figure 5.7(a) is a typical double peak load curve with the higher peak occurring at night for PJM system on Nov. 23, 2014. Here, the total system peak load is 1050 MW and equally distributed at Buses B, C and D. The hourly optimal coupon prices without FTR and with FTR are shown in Figure 5.7(b), the optimal demands are in Figure 5.7(c) and the hourly profits are depicted in Figure 5.7(d). In this simulation, the FTR is from Bus E to D with 200 MW.

Figure 5.7(b) demonstrates that when the LSE holds 200 MW FTR from Bus E to D, the coupon prices offered to customers decrease. Without FTR, the LSE offers a higher coupon price such as \$10/MWh during the peak hours from 8 AM to 17 PM and from 21 PM to 23 PM to stimulate the customers to reduce their electricity demand. While with this FTR holding, the LSE's coupon price decreases.

Figure 5.7(c) shows that, with the help of FTR, the LSE can bid higher demand to the ISO. And with the FTR considered in the bidding process, the LSE has the opportunity to obtain

more profit as shown in Figure 5.7(d). FTR provides more flexibility to the LSE to obtain a higher profit if it is considered in the LSE's strategic bidding model with CBDR.

Table 5.2 Bidding results with Different FTR paths

FTR path	R (\$)	Opt. D (MW)	Opt. Coupon (\$/MWh)	Bus LMP (\$/MWh)				
				A	B	C	D	E
None	2086.4	276.5	10	10.36	10.85	11.03	11.55	10.00
A-D	2562.6	284.9	6	10.75	11.75	12.14	13.20	10.00
B-D	2307.6	280.3	8	10.52	11.21	11.48	12.21	10.00
C-D	2240.7	276.5	10	10.36	10.85	11.04	11.55	10.00
E-D	3000	300	0	12.38	15.58	16.82	20.21	10.00

5.5.3 IEEE 39-bus System

IEEE 39-bus system integrated with 3 wind farms is shown in [131]. This system has ten generators with total capacity of 7367 MW and total demand is 6254 MW. The detail system parameters are in [107]. Three wind farms are integrated to bus 11, 24 and 26. The generation parameter is in Table 5.3. Four transmission lines are applied to the following thermal limits: 800MW for lines 1-39, 500MW for lines 2-3, 500MW for lines 3-18, and 600MW for lines 16-17.

At the operating point investigated in this study, assume that the forecast wind power outputs are 360 MW for three wind farms under a normal distribution with 36 MW as its standard deviation. The expected bus LMPs considering three wind farms' power output uncertainty under original load level is shown in Figure 5.8(a).

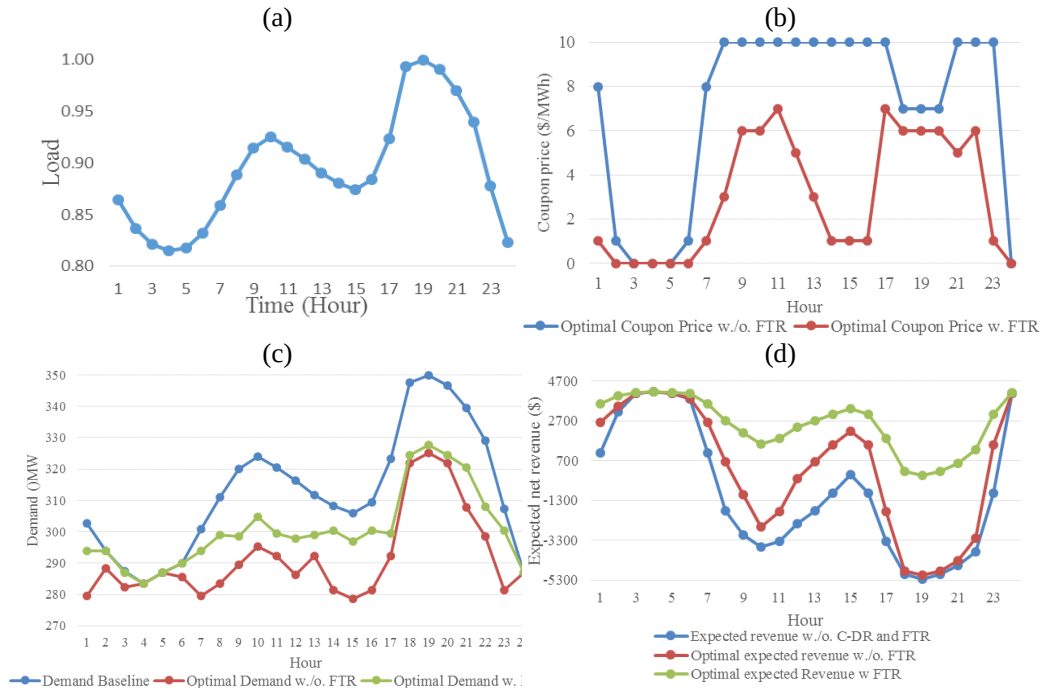


Figure 5.7 Daily load curve and optimal coupon prices, demand and expected net revenue at different hours w/o. FTR and w. FTR

Table 5.3 Generation parameter

Unit	Price (\$/MWh)	Pmax	Unit	Price (\$/MWh)	Pmax
1	10	1040	6	27	687
2	15	646	7	28	580
3	16	725	8	11	564
4	25	652	9	12	865
5	26	508	10	17	1100

In this study, the LSE bidder contains the demand under Bus 20, 21, 23 and 24 and the electricity flat rate offered to the customers are \$26/MWh. The coupon price varies from \$0.5/MWh to \$2.5/MWh with \$0.5/MWh as the increment step. From the expected LMPs in Figure 5.8(a), it demonstrates that Bus 2 (Bus 30 is equivalent with Bus 2) and Bus 25 (Bus 37 is equivalent with Bus 25) have the largest LMP difference with the LSE's buses. From the conclusion in the previous subsection that the largest LMP difference can impact the bidding results obviously, the impact of FTR holding from Bus 2 to Bus 20 and Bus 25 to Bus 21 on the LSE's strategic bidding with CBDR will be investigated.

Figure 5.8(b) demonstrates the optimal coupon prices under different FTR holding. Similar with the observation in Figure 5.5, it shows that the optimal coupon price decrease with the FTR amounts on these two FTR paths. Figure 5.8(c) is the optimal expected revenue under different FTR holding. Obviously the optimal expected revenue of the LSE bidder increases with FTR amounts.

Table 5.4 Dispatched load, LMP on buses and LSE's Revenue under different Coupon Prices
with 400 MW FTR on each Path

Coupon (\$/MWh)	Dispatched Load (MW)				LMP (\$/MWh)	Revenue (\$)
	Bus 20	Bus 21	Bus 23	Bus 24		
0	680	274	247.5	308.6	26.984	11217.139
0.5	645.093	259.564	234.460	293.340	26.700	11436.306
1.0	643.358	255.641	230.917	287.908	26.582	11464.220
1.5	637.348	253.034	227.236	283.218	26.476	11473.769
2.0	626.214	248.886	223.155	278.245	26.346	11467.517
2.5	622.396	245.622	220.025	274.342	26.254	11418.169

TABLE 5.4 is the example of load dispatch results, LMPs on the LSE's buses and expected revenue with 400 MW FTR on each path. With this FTR holding, the optimal coupon price is \$1.5/MWh and the corresponding expected revenue is \$11,473.769. TABLE 5.5 is the results of optimal dispatched load and LMPs on the LSE's bus, optimal coupon price and LSE's expected revenue under different FTR amount for both paths. As shown in Figure 5.8(b) and TABLE 5.5, the optimal coupon price decreases with the FTR amount on both paths. With a higher FTR holding, the LSE bidder has fewer incentive to reduce its demand on buses to reduce the LMPs. Although this will lead a loss of the electricity payment from the customers, the revenue loss under this higher LMPs can be compensated with the higher FTR revenue from congestion surplus.

Table 5.5 Dispatched load, LMP on buses, Optimal Coupon Price and LSE's R under different FTR Amount on each Path

FTR (MW)	Dispatched Load (MW)				LMP (\$/MWh)	Opt. Coupon	Revenue (\$)
	Bus 20	Bus 21	Bus 23	Bus 24			
0	610.683	243.150	219.634	273.150	26.214	2.5	724.829
100	610.683	243.150	219.634	273.150	26.214	2.5	2308.135
200	621.135	247.049	223.155	277.857	26.328	2.0	5356.810
300	626.214	248.886	223.155	277.857	26.345	2.0	8410.752
400	637.348	253.034	227.236	283.218	26.476	1.5	11473.769
500	643.358	255.641	239.917	287.908	26.582	1.0	14565.368
600	645.093	259.564	234.460	292.340	26.700	0.5	17681.794

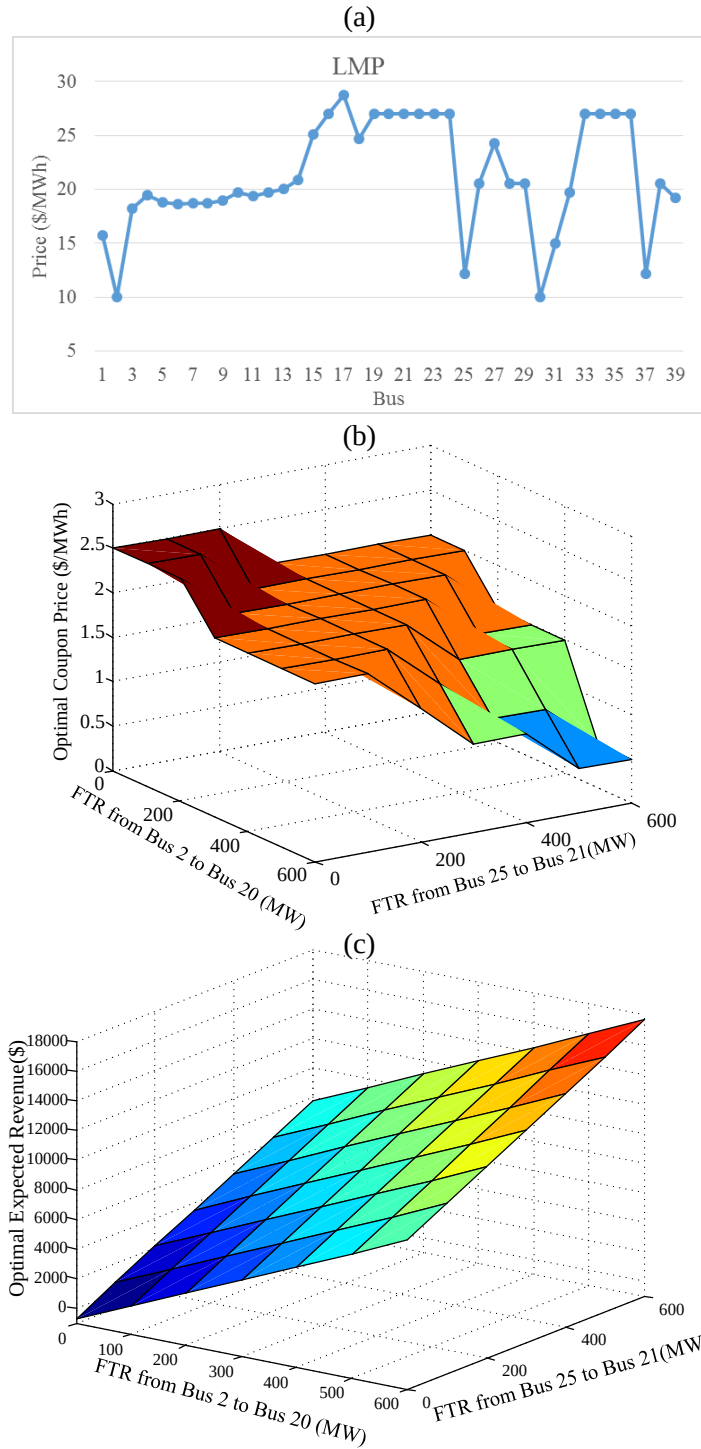


Figure 5.8 Expected bus LMPs considering wind uncertainty and Optimal coupon price and expected net revenue under different FTR holding

5.6 Conclusions

In this chapter, a strategic bidding approach for the LSE considering the impact of FTR and CBDR is proposed. In this model, the uncertainty of wind power output and customers' electricity consumption behavior patterns toward different coupon prices are included. The main contributions of this work can be summarized as follows:

- 1) FTR's congestion compensation is modeled in the LSEs' strategic bidding process. This model utilizes a bi-level optimization and by recasting the lower-level problem into the KKT optimality condition, this bi-level problem is transformed to a MPEC problem, then further converted into a MILP problem which can be solved using available software tools.
- 2) The impact of FTR on the strategic bidding of LSE with CBDR is analyzed with different FTR paths. It demonstrates that FTR's influence on LSEs' strategic bidding results varies w.r.t. different FTR paths. The impact increases with the LMP differences between the injection and the delivery buses of FTRs' paths.
- 3) With an increasing FTR amount, the coupon prices which the LSE offers to customers are prone to decrease if the FTR holding can impact the bidding results. Under this circumstance, the LSE's incentive to stimulate customers to reduce their demand is decreasing with its FTR holding amount.
- 4) The simulation results demonstrate the benefit of the congestion compensation of FTR under high load level and the profit obtained from the LMP reduction through CBDR should be co-optimized. Also, LSEs can obtain higher profit by considering FTR in its bidding process.

Furthermore, it should be noted that although this chapter discuss the impact of FTR on

the LSE's strategic bidding considering CBDR. The results can be utilized to determine the profitable FTR path and the FTR bidding curve which is valuable for LSEs to participate in ISO's FTR auction process. Also the potential impact of FTR on DA market should be considered in the LSE's FTR bidding model and this should be the future work.

CHAPTER 6

STRATEGIC SCHEDULING OF ENERGY STORAGE FOR LOAD SERVING ENTITIES IN LMP MARKET

6.1 Introduction

The energy industry has recently stepped into the era of developing large amounts of renewables and numerous smart grid technologies. Laying out a road map towards a modern and cleaner grid is the task for ISOs, utilities and regulators. In the United States, wind capacity as a percentage of the total generation capacity increased from 1.1% in 2006 to 3.6% in 2010 [132]. Meanwhile, ISO-managed markets also see significant wind percentage growth in terms of the generation portfolio capacity. Electric Reliability Council of Texas (ERCOT), Midcontinent Independent System Operator (MISO) and California Independent System Operator (CAISO) are the top three ISO-managed markets with the highest levels of wind penetration [133].

Major challenges arise from the intermittent nature of wind power and the “non-dispatchability” of wind resources in electric power market operations. The utilization of energy storage to increase operational flexibility is commonly regarded as a logical complement for systems with large amounts of wind power. Therefore, regulators and policy makers have started to investigate the impact and benefit of energy storage integrated into the grid and have initiated some pilot procurement mandates for load serving entities (LSEs) such as utility companies. As LSEs’ ES procurement becomes inevitable with increasing scale in the near future, there exists opportunities for LSE to better understand how to optimally schedule ES to get more investment return or to reduce ratepayer’s cost.

In general, the capability of storing energy electricity and releasing it during the more profitable periods would result in some serious business strategy when more ES devices come into participants' portfolio. In a vertically integrated utility company, ES can be used to coordinate with the company's thermal plants. In a competitive electricity market, an individual ES owner can purchase energy and sell it either on a Day-Ahead (DA) market or a spot market or through bilateral contracts. It can also participate in multi-markets such as energy and ancillary service markets [134]–[139].

Under current practice, the evaluation of energy storage from an LSE's perspective would normally include a price-based dispatch and analysis of its cash flow for an extended period of time, i.e., from a few years up to 20 or even 30 years. A pre-defined or forecasted price forward curve is given first. Then, energy and ancillary market co-optimization is performed to determine the profitability of the energy storage. Although the lack of interaction between ES operating mode and wholesale electricity clearing prices could stand now, it might not necessarily hold true going forward. California Public Utility Commission (CPUC) has established rules that require all the utilities and other LSEs to procure more than 1,300 MW of energy storage by 2020, i.e., roughly 3%~4% of CAISO's summer peak load [140]. Considering the increase in ES penetration will certainly be able to alter the supply/demand curve someday, it is important to investigate the dynamics between ES scheduling mode and market clearing prices.

There are some existing research works in the literatures. For instance, in [141]–[146] different types of ES devices such as pumped storage units, compressed air and hydrogen-based energy storage, are utilized by wind generation to mitigate their power output intermittence and gain extra profits from the deregulated electricity market like the day-ahead (DA) market. In

[147], the sizing optimization approach of energy storage for microgrid is proposed based on discrete Fourier transform (DFT). In [148], the impact and benefit of ES in the Netherlands electricity supply integrating for large-scale wind power is investigated from the viewpoint of system and market operators. A robust optimization method for ES investment in the transmission networks considering the system uncertainties is proposed in [149]. The charging portfolio optimization for plug-in electric vehicles (PEVs), another form of ES which has an increasing penetration, is proposed in [150]–[152]. The ES scheduling methods proposed in these research works are from the viewpoints of the wind power generation company, the market operators, or the ES devices like PEV themselves. In the near future, LSEs such as the utility companies may also play an important role in utilizing ES in their power procurement optimization. Another concern is that ES scheduling is based on the forecast prices in these work and the price dynamics that the impact of ES charging/discharging on the system prices cannot be modelled in these approaches. With the capacity and penetration of ES increasing in the system, this impact should be considered in the market participants' operations including ES.

Therefore, this chapter proposes a bi-level optimization model with LSE's main objective being its profit maximization that also simulates the ISO/RTO's Day-Ahead market clearing process, which is modelled as a dc optimal power flow (DCOPF) problem. In this model, the Locational Marginal Price (LMP) is the key variable for the determination of ES revenue, and the impact of ES scheduling decision on LMPs is endogenously modelled. The coupling effect makes the model essentially nonconvex and more challenging to solve than normal mathematical programs. The lower level, ISO's economic dispatch problem, of the proposed model can be stated as its Karush-Kuhn-Tucker (KKT) optimality conditions and the bi-level optimization model is an instance of mathematical program with equilibrium constraints (MPEC), which

could be further converted to a mixed integer programming problem (MILP) and solved by commercial optimization software [91], [103]–[105], [130].

The rest of this chapter is organized as follows: Section 2 presents the traditional scheduling model based on forecasted prices and the proposed bi-level model of ES strategic scheduling for LSEs. Section 3 proposes the actual solution to solve the stochastic bi-level model including the procedure of transforming it into MPEC and the conversion from MPEC to mixed integer linear programming (MILP) problem. Section 4 demonstrates the simulation results and numerical analysis on the PJM 5-bus system and the IEEE 118-bus system to clearly verify the proposed method. Section 5 presents the concluding remarks and points out some future work.

6.2 Strategic Energy Storage Scheduling for LSEs

The three-layer electricity market framework and the structure of LSEs including ES is shown in Figure 6.1. The details of an LSE's strategic scheduling for ES under this market structure will be discussed later.

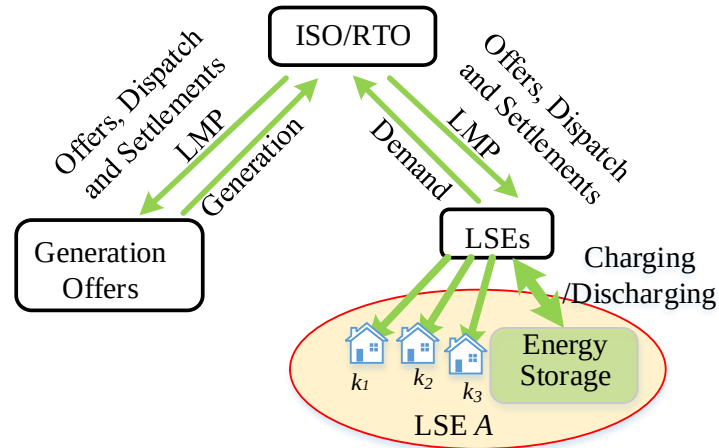


Figure 6.1 Structure of the electricity market and LSEs with ES

6.2.1 Net Revenue of Load Serving Entities considering ES

The LSE receives a gross revenue from each hour, t , at bus i , given by the product of retail price $\eta_{i,t}$ and the electricity consumption $D_{i,t}^0$. Then, the payment (i.e., the product of spot price $\pi_{i,t}$ and the electricity bid $D_{i,t}$) is subtracted since the LSE pays this amount to the ISO/regional system operator (RTO) in the wholesale market for purchasing electricity at volatile nodal prices ($\pi_{i,t}$). Therefore, the net revenue of a LSE is in (6.1),

$$R_n = \sum_{t=1}^{24} \left[\sum_{i \in A} \left(\eta_{i,t} \cdot D_{i,t}^0 - \pi_{i,t} \cdot D_{i,t} \right) \right] \quad (6.1)$$

If the LSE has no capability to change its load, the electricity bid $D_{i,t}$ should be equal to the electricity consumption $D_{i,t}^0$ to maintain the consumers' reliable electricity consumption. If the LSE installs some ES system at some of its buses, and assumes that the discharging power of energy storage is positive whereas the charging power is negative, and in this case the demand bids on energy storage buses can be expressed as

$$D_{i,t} = D_{i,t}^0 - S_{i,t}, \forall i \in SC \quad (6.2)$$

where $D_{i,t}^0$ is the forecast demand on the buses of LSE bidder and $D_{i,t}$ is the demand that the LSE bids in ISO's Day ahead market.

If the LSE has some ES installed at some buses shown in Figure 6.1 (Set SC identifies the buses equipped with ES), the total revenue of a LSE with energy storage can be expressed as follows,

$$R_n = \sum_{t=1}^{24} \left[\sum_{i \in A} (\eta_{i,t} - \pi_{i,t}) \times D_{i,t}^0 + \sum_{i \in SC} \pi_{i,t} \times S_{i,t} \right] \quad (6.3)$$

This model is a general model for an LSE utilizing energy storage in the day-ahead

market.

6.2.2 Traditional Scheduling of Energy Storage System

Traditionally, the daily scheduling of energy storage system [153] is based on the forecasted demand and LMP. $D_{i,t}^0$ and $\pi_{i,t}$ are forecasted and constant. The model for energy storage scheduling in this situation is expressed in (6.4a)-(6.4g). In the scheduling process, the decision variables are the 24 hours ES charging/discharging power output schedules $P_{si,t}^c, P_{si,t}^d$.

$$\textbf{Maximize (6.3)} \quad (6.4a)$$

$$\text{s.t. Constraint (6.2)} \quad (6.4b)$$

$$S_{i,t} = P_{si,t}^d - P_{si,t}^c \quad (6.4c)$$

$$(E_i^{\min} - E_{i0}) \leq \sum_{\tau=1}^t (\zeta_c P_{si,\tau}^c - \frac{1}{\zeta_d} P_{si,\tau}^d) \leq (E_i^{\max} - E_{i0}), i \in SC, \quad t = 1, \dots, 24 \quad (6.4d)$$

$$0 \leq P_{si,t}^c \leq P_{si}^{c(\max)} \alpha_{i,t}^c \quad (6.4e)$$

$$0 \leq P_{si,t}^d \leq P_{si}^{d(\max)} \alpha_{i,t}^d \quad (6.4f)$$

$$\alpha_{i,t}^c + \alpha_{i,t}^d \leq 1 \quad (6.4g)$$

where $E_i^{\min}$ and $E_i^{\max}$ is the minimum and maximum ES capacity status, respectively, at bus i ; $P_{si}^{c(\max)}$ and $P_{si}^{d(\max)}$ is the maximum charging/discharging power of ES devices; equation (6.4b) is the actual demand at ES buses; (6.4c) is the power output of ES (ES's power output is positive for discharging and negative for charging); (6.4d) is the dynamic capacity limit of ES system; (6.4e) and (6.4f) are the charging/discharging power output limit; and (6.4g) is the charging/discharging status constraint (only one status is active at a specific time).

6.2.3 Bi-level Model for Strategic Scheduling of Energy Storage

The objective of the LSE strategic scheduling for energy storage (ES) system is to maximize its net revenue considering the impact of ES on the LMPs. In this process, the decision variables are still the 24-hour schedules of ES charging/discharging power output. In this strategic scheduling model, the bus LMP are obtained from ISO's day ahead economic dispatch. Therefore, the strategic scheduling problem is formulated as a bi-level problem in (6.5a)-(6.5g), where A is an LSE strategic bidder whose customers may be connected at several buses shown in Figure 6.1.

$$\textbf{Maximize (6.3)} \quad (6.5a)$$

$$\text{s.t. Constraints (6.4b)-(6.4g)} \quad (6.5b)$$

$$\forall \pi_i \in \arg \left\{ \min \sum_{t=1}^{24} \sum_{i=1}^N c_{i,t} \times G_{i,t} \right\} \quad (6.5c)$$

$$\text{s.t. } \sum_{i=1}^N G_{i,t} = \sum_{i=1}^N D_{i,t} : \lambda_t \quad (6.5d)$$

$$-Limit_l \leq \sum_{i=1}^N GSF_{l-i} \times (G_{i,t} - D_{i,t}) \leq Limit_l : \mu_{l,t}^{\min}, \mu_{l,t}^{\max}, \quad (6.5e)$$

$$\forall l = 1, 2, \dots, M$$

$$G_i^{\min} \leq G_{i,t} \leq G_i^{\max} : \omega_{i,t}^{\min}, \omega_{i,t}^{\max}, \forall i = 1, 2, \dots, N \quad (6.5f)$$

$$\left. \begin{aligned} &RR_i^{\min} \leq G_{i,t+1} - G_{i,t} \leq RR_i^{\max} : \xi_{i,t}^{\min}, \xi_{i,t}^{\max}, \\ &\forall i = 1, 2, \dots, N, \forall t = 1, 2, \dots, 23 \end{aligned} \right\} \quad (6.5g)$$

$$\begin{aligned}
L(\mathbf{x}) = & \sum_{t=1}^{24} \left\{ \sum_{i=1}^N c_{i,t} \times G_{i,t} - \lambda_t \times \left[\sum_{i=1}^N G_{i,t} - \sum_{i=1}^N D_{i,t} \right] \right. \\
& - \sum_{l=1}^M \mu_{l,t}^{\max} \times \left[Limit_l - \sum_{i=1}^N GSF_{l-i} \times (G_{i,t} - D_{i,t}) \right] \\
& - \sum_{l=1}^M \mu_{l,t}^{\min} \times \left[Limit_l + \sum_{i=1}^N GSF_{l-i} \times (G_{i,t} - D_{i,t}) \right] \\
& - \sum_{i=1}^N \left[\omega_{i,t}^{\max} \times (G_i^{\max} - G_{i,t}) + \omega_{i,t}^{\min} \times (G_{i,t} - G_i^{\max}) \right] \Big\} \\
& - \sum_{t=1}^{23} \sum_{i=1}^N \left[\xi_{i,t}^{\max} \times (RR_i^{\max} - G_{i,t+1} + G_{i,t}) \right. \\
& \left. + \xi_{i,t}^{\min} \times (G_{i,t+1} - G_{i,t} - RR_i^{\min}) \right]
\end{aligned} \tag{6.5h}$$

$$\pi_{i,t} = \lambda_t + \sum_{l=1}^M GSF_{l-i} (\mu_{l,t}^{\min} - \mu_{l,t}^{\max}) \tag{6.5i}$$

where (6.5b) is the constraint for ES which is the same as traditional scheduling in the previous subsection; (6.5c)-(6.5g) represent the ISO's 24 hours economic dispatch (ED) model which determines the optimal generation dispatch as well as the LMPs; (6.5h) is the Lagrangian function of ISO's economic dispatch model (6.5c)-(6.5g) and (6.5i) is the formulation of LMP. Note, (6.5c) is the ISO's 24-hour generation cost; equation (6.5d) represents the system generation and demand balance at time t ; (6.5e) is the branch flow upper and lower limits; (6.5f) is the generation output maximum and minimum limits; (6.5g) is the generation ramp limits. The variables on the right side of the colons are the dual variables associated with the corresponding equality or inequality constraints on the left side of the colons.

The LMP $\pi_{i,t}$, which is the partial derivative of the Lagrangian function of ISO's economic dispatch model to the nodal demand, can be obtained from the dual variables of the optimal solution of ISO's economic dispatch. The Lagrangian function is in (6.5h) and the LMP formulation is in (6.5i). The LMP $\pi_{i,t}$ from the ED depends on demand, $D_{i,t}$, as well as the bid

prices/quantities of generators.

6.2.4 Baseline Demand Model

In this subsection, the baseline demand model which corresponds to the D^0 in Eq. (6.2) will be presented. Based on the forecast of this load level, the LSE optimizes the output of ES to participate in the day ahead market and to obtain maximum profit.

The energy storage schedules are critically dependent on the customers' demand baseline [93] from which the demand bids according to ES charging/discharging can be calculated. Due to the strong cyclic pattern of customers' electricity consumption over time [94], the demand baseline can be obtained from historical data. For instance, the Southern California Edison (SCE) utility employs an approach called the "10-Day Average Baseline" [95]. More details concerning the baseline calculation have been introduced in [96]. However, it is out of the research scope of this chapter to discuss the pros and cons of various consumer demand baseline methods.

6.3 Mathematical Solution of the Proposed Model

As presented in Section 2, the strategic scheduling of ES in (6.5a) to (6.5g) is formulated as a bi-level optimization problem. The upper level is to maximize the LSE's profit; and the lower level is to minimize the generation cost to model the ISO's DA market-clearing process.

Due to the existence of dependent variables in each level, these two optimization problems are coupled. For instance, the LMP in the upper level problem is decided by the lower level problem of ISO's market clearing process, while the demands at ES buses in the lower level market clearing problem depend on the upper level. In this chapter, dc optimal power flow (DCOPF) is implemented to clear the ISO's DA market. Due to the linearity of DCOPF [3], [82], [90], [121], [129], its optimal solution should be unique and satisfies the Karush-Kuhn-Tucker (KKT) optimality conditions. Consequently, the bi-level optimization problem is formulated as a

mathematical program with equilibrium constraints (MPEC) by integrating the lower level problem into the upper level problem using its KKT conditions as the extra complementarity constraints [124]. According to the strong duality theory, this MPEC model can be converted to an MILP that is solvable by available software.

6.3.1 Formulation of an MPEC

Given that the lower level problem is a LP problem, the bi-level strategic ES scheduling model can be transformed to a single level MPEC problem by recasting the lower level problem as its KKT optimality conditions, then adding them into the upper level problem as a set of additional complementarity constraints.

$$\textbf{Maximize (6.5a)} \quad (6.6a)$$

$$\text{s.t. Constraint in (6.5b)} \quad (6.6b)$$

$$c_{i,t} = \lambda_t + \sum_{l=1}^M GSF_{l-i} \times (\mu_{l,t}^{\min} - \mu_{l,t}^{\max}) + \omega_{i,t}^{\min} - \omega_{i,t}^{\max} + \xi_{i,t}^{\max} - \xi_{i,t}^{\min}, \forall t = 1 \quad (6.6c)$$

$$c_{i,t} = \lambda_t + \sum_{l=1}^M GSF_{l-i} \times (\mu_{l,t}^{\min} - \mu_{l,t}^{\max}) + \omega_{i,t}^{\min} - \omega_{i,t}^{\max} + \xi_{i,t}^{\max} - \xi_{i,t}^{\min} + \xi_{i,t-1}^{\min} - \xi_{i,t-1}^{\max}, \quad (6.6d)$$

$$\forall t = 2, \dots, 23$$

$$c_{i,t} = \lambda_t + \sum_{l=1}^M GSF_{l-i} \times (\mu_{l,t}^{\min} - \mu_{l,t}^{\max}) + \omega_{i,t}^{\min} - \omega_{i,t}^{\max} + \xi_{i,t-1}^{\min} - \xi_{i,t-1}^{\max}, \forall t = 24 \quad (6.6e)$$

$$0 \leq \mu_{l,t}^{\min} \perp \text{Limit}_l + \sum_{i=1}^N GSF_{l-i} \times (G_{i,t} - D_{i,t}) \geq 0, \forall l = 1, \dots, M; \forall t = 1, \dots, 24 \quad (6.6f)$$

$$0 \leq \mu_{l,t}^{\max} \perp \text{Limit}_l - \sum_{i=1}^N GSF_{l-i} \times (G_{i,t} - D_{i,t}) \geq 0, \forall l = 1, \dots, M; \forall t = 1, \dots, 24 \quad (6.6g)$$

$$0 \leq \omega_{i,t}^{\min} \perp G_{i,t} - G_i^{\min} \geq 0, \forall t = 1, \dots, 24 \quad (6.6h)$$

$$0 \leq \omega_{i,t}^{\max} \perp G_i^{\max} - G_{i,t} \geq 0, \forall t = 1, \dots, 24 \quad (6.6i)$$

$$0 \leq \xi_{i,t}^{\min} \perp G_{i,t+1} - G_{i,t} - RR_i^{\min} \geq 0, \forall t = 1, \dots, 23 \quad (6.6j)$$

$$0 \leq \xi_{i,t}^{\max} \perp RR_i^{\max} - G_{i,t+1} + G_{i,t} \geq 0, \forall t = 1, \dots, 23 \quad (6.6k)$$

where the perpendicular sign $\perp$ denotes a zero cross product of the corresponding variables in vector form.

6.3.2 Mixed-integer Linear Programming (MILP)

The model (6.6a)-(6.6k) is nonlinear due to the product term $\pi_{i,t} \times S_{i,t}$ (both $\pi_{i,t}$ and $S_{i,t}$ are variables) in the objective function and the complementarity constraints (6.6f)-(6.6k). According to the strong duality theory, the objective of the primal problem is equal to the objective of the corresponding dual problem. For the ED problem (6.5c)-(6.5g), the relationship between the objectives of the dual and primal problems can be expressed as follows:

$$\begin{aligned} & \sum_{t=1}^{24} \left\{ \lambda_t \times \sum_{i=1}^N D_{i,t} + \sum_{l=1}^M \mu_{l,t}^{\max} \times (-Limit_l - \sum_{i=1}^N GSF_{l-i} \times D_{i,t}) \right. \\ & \quad \left. + \sum_{l=1}^M \mu_{l,t}^{\min} \times (-Limit_l + \sum_{i=1}^N GSF_{l-i} \times D_{i,t}) + \sum_{i=1}^N [\omega_{i,t}^{\max} \times (-G_{i,t}^{\max}) + \omega_i^{\min} \times G_{i,t}^{\min}] \right\} \\ & \quad + \sum_{t=1}^{23} \sum_{i=1}^N [\xi_{i,t}^{\max} \times (-RR_i^{\max}) + \xi_{i,t}^{\min} \times RR_i^{\min}] = \sum_{t=1}^{24} \sum_{i=1}^N c_{i,t} \times G_{i,t} \end{aligned} \quad (6.7)$$

Consider Equation (6.2),

$$\begin{aligned} & \sum_{t=1}^{24} \left\{ \lambda_t \times \left(\sum_{i \in SC} (D_{i,t}^0 - S_{i,t}) + \sum_{i \notin SC} D_{i,t} \right) + \sum_{l=1}^M \mu_{l,t}^{\max} \times \left[-Limit_l - \sum_{i \in SC} GSF_{l-i} \times (D_{i,t}^0 - S_{i,t}) - \sum_{i \notin SC} GSF_{l-i} \times D_{i,t} \right] \right. \\ & \quad \left. + \sum_{l=1}^M \mu_{l,t}^{\min} \times \left[-Limit_l + \sum_{i \in SC} GSF_{l-i} \times (D_{i,t}^0 - S_{i,t}) + \sum_{i \notin SC} GSF_{l-i} \times D_{i,t} \right] + \sum_{i=1}^N [\omega_{i,t}^{\max} \times (-G_{i,t}^{\max}) + \omega_i^{\min} \times G_{i,t}^{\min}] \right\} \\ & \quad + \sum_{t=1}^{23} \sum_{i=1}^N [\xi_{i,t}^{\max} \times (-RR_i^{\max}) + \xi_{i,t}^{\min} \times RR_i^{\min}] = \sum_{t=1}^{24} \sum_{i=1}^N c_{i,t} \times G_{i,t} \end{aligned} \quad (6.8)$$

Taking the LMP expression in (6.5i), the product term $\pi_{i,t} \times S_{i,t}$ in (6.5a) can be transformed

as (6.9).

$$\sum_{t=1}^{24} \sum_{i \in SC} \pi_{i,t} \times S_{i,t} = \sum_{t=1}^{24} \left[\lambda_t \times \sum_{i \in SC} S_{i,t} + \sum_{l=1}^M \sum_{i \in SC} GSF_{l-i} (\mu_l^{\min} - \mu_l^{\max}) \times S_{i,t} \right] \quad (6.9)$$

Substituting (6.9) into (6.8) renders,

$$\begin{aligned} \sum_{t=1}^{24} \sum_{i \in SC} \pi_{i,t} \times S_{i,t} = & \sum_{t=1}^{24} \left\{ \lambda_t \times \left(\sum_{i \in SC} D_{i,t}^0 + \sum_{i \notin SC} D_{i,t} \right) \right. \\ & + \sum_{l=1}^M \mu_{l,t}^{\max} \times (-Limit_l - \sum_{i \in SC} GSF_{l-i} \times D_{i,t}^0 - \sum_{i \notin SC} GSF_{l-i} \times D_{i,t}) \\ & + \sum_{l=1}^M \mu_{l,t}^{\min} \times (-Limit_l + \sum_{i \in SC} GSF_{l-i} \times D_{i,t}^0 + \sum_{i \notin SC} GSF_{l-i} \times D_{i,t}) \\ & + \sum_{i=1}^N \left[\omega_{i,t}^{\max} \times (-G_{i,t}^{\max}) + \omega_i^{\min} \times G_{i,t}^{\min} \right] - \sum_{i=1}^N c_{i,t} \times G_{i,t} \left. \right\} \\ & + \sum_{t=1}^{23} \sum_{i=1}^N \left[\xi_{i,t}^{\max} \times (-RR_i^{\max}) + \xi_{i,t}^{\min} \times RR_i^{\min} \right] \end{aligned} \quad (6.10)$$

Therefore, the objective in (6.5a) can be expressed as (6.10) and the MPEC problem is converted as a MILP problem as:

$$\max R_n = \sum_{t=1}^{24} \left[\sum_{i \in A} (\eta_{i,t} - \pi_{i,t}) \times D_{i,t}^0 + \pi_{i,t} \times S_{i,t} \right] \quad (6.11a)$$

and

$$\begin{aligned} R_n = & \sum_{t=1}^{24} \left\{ \sum_{i \in A} (\eta_{i,t} - \pi_{i,t}) \times D_{i,t}^0 + \lambda_t \times \left(\sum_{i \in SC} D_{i,t}^0 + \sum_{i \notin SC} D_{i,t} \right) \right. \\ & + \sum_{l=1}^M \left[\mu_{l,t}^{\max} \times \left(-Limit_l - \sum_{i \in SC} GSF_{l-i} \times D_{i,t}^0 - \sum_{i \notin SC} GSF_{l-i} \times D_{i,t} \right) \right] \\ & + \sum_{l=1}^M \left[\mu_{l,t}^{\min} \times \left(-Limit_l + \sum_{i \in SC} GSF_{l-i} \times D_{i,t}^0 + \sum_{i \notin SC} GSF_{l-i} \times D_{i,t} \right) \right] \\ & + \sum_{i=1}^N \left[\omega_{i,t}^{\max} \times (-G_{i,t}^{\max}) + \omega_i^{\min} \times G_{i,t}^{\min} \right] - \sum_{i=1}^N c_{i,t} \times G_{i,t} \left. \right\} \\ & + \sum_{t=1}^{23} \sum_{i=1}^N \left[\xi_{i,t}^{\max} \times (-RR_i^{\max}) + \xi_{i,t}^{\min} \times RR_i^{\min} \right] \end{aligned} \quad (6.11b)$$

$$\text{s.t. Constraints in (6.6b)-(6.6e)} \quad (6.11c)$$

$$0 \leq \mu_{l,t}^{\min} \leq M_{\mu}^{\min} v_{\mu,l,t}^{\min} \quad (6.11d)$$

$$0 \leq Limit_l + \sum_{i=1}^N GSF_{l-i} \times (G_{i,t} - D_{i,t}) \leq M_{\mu}^{\min} (1 - v_{\mu,l,t}^{\min}) \quad (6.11e)$$

$$0 \leq \mu_{l,t}^{\max} \leq M_{\mu}^{\max} v_{\mu,l,t}^{\max} \quad (6.11f)$$

$$0 \leq Limit_l - \sum_{i=1}^N GSF_{l-i} \times (G_{i,t} - D_{i,t}) \leq M_{\mu}^{\max} (1 - v_{\mu,l,t}^{\max}) \quad (6.11g)$$

$$0 \leq \omega_{i,t}^{\min} \leq M_{\omega}^{\min} v_{\omega,i,t}^{\min} \quad (6.11h)$$

$$0 \leq G_{i,t} - G_i^{\min} \leq M_{\omega}^{\min} (1 - v_{\omega,i,t}^{\min}) \quad (6.11i)$$

$$0 \leq \omega_{i,t}^{\max} \leq M_{\omega}^{\max} v_{\omega,i,t}^{\max} \quad (6.11j)$$

$$0 \leq G_i^{\max} - G_{i,t} \leq M_{\omega}^{\max} (1 - v_{\omega,i,t}^{\max}) \quad (6.11k)$$

$$0 \leq \xi_{i,t}^{\min} \leq M_{\xi}^{\min} v_{\xi,i,t}^{\min} \quad (6.11l)$$

$$0 \leq G_{i,t+1} - G_{i,t} - RR_i^{\min} \leq M_{\xi}^{\min} (1 - v_{\xi,i,t}^{\min}) \quad (6.11m)$$

$$0 \leq \xi_{i,t}^{\max} \leq M_{\xi}^{\max} v_{\xi,i,t}^{\max} \quad (6.11n)$$

$$0 \leq RR_i^{\max} - G_{i,t+1} + G_{i,t} \leq M_{\xi}^{\max} (1 - v_{\xi,i,t}^{\max}) \quad (6.11o)$$

where $M_{\mu}^{\min}$, $M_{\mu}^{\max}$, $M_{\omega}^{\min}$, $M_{\omega}^{\max}$, $M_{\xi}^{\min}$ and $M_{\xi}^{\max}$ are large enough constants, and $v_{\mu,l,t}^{\min}$, $v_{\mu,l,t}^{\max}$, $v_{\omega,i,t}^{\min}$, $v_{\omega,i,t}^{\max}$, $v_{\xi,i,t}^{\min}$, and $v_{\xi,i,t}^{\max}$ are the auxiliary binary variables [64]. Note that the retail price $\eta_{i,t}$ is fixed in this chapter and is a constant in the optimization model [81], [124]. The objective of the LSE bidder is to maximize its own profit through strategic scheduling of ES under the electricity flat rate, which is the common electricity payment method right now. However, the flexible retail price mechanism can be included in this work and it will be part of our future work.

6.3.3 Model Extensions to Integrate Uncertainty

In this subsection, the extensions of the above model, including the uncertainty of wind power and demand, will be discussed. The forecasted wind power production and demand are expressed as a set of probabilistic scenarios ($s = 1 \sim S$) with a probability set of $\{p_s\}$.

The scenario below is one example of an ED model that includes wind power and demand uncertainty.

$$\min \sum_{t=1}^{24} \sum_{i=1}^N c_{i,t} \times G_{i,t}^s \quad (6.12a)$$

$$\text{s.t. } \sum_{i=1}^N G_{i,t}^s = \sum_{i=1}^N D_{i,t}^s : \lambda_t^s \quad (6.12b)$$

$$D_{i,t}^s = D_{i,t}^{0,s} - S_{i,t}, \forall i \in A \quad (6.12c)$$

$$-Limit_l \leq \sum_{i=1}^N GSF_{l-i} \times (G_{i,t}^s - D_{i,t}^s) \leq Limit_l : \mu_{l,t}^{s,\min}, \mu_{l,t}^{s,\max}, \forall l = 1, 2, \dots, M \quad (6.12d)$$

$$G_i^{\min} \leq G_{i,t}^s \leq G_i^{\max} : \omega_{i,t}^{s,\min}, \omega_{i,t}^{s,\max}, \forall i = 1, 2, \dots, N \quad (6.12e)$$

$$RR_i^{\min} \leq G_{i,t+1}^s - G_{i,t}^s \leq RR_i^{\max} : \xi_{i,t}^{s,\min}, \xi_{i,t}^{s,\max}, \forall i = 1, 2, \dots, N, \forall t = 1, 2, \dots, 23 \quad (6.12f)$$

where $G_{i,t}^s$ is the generation dispatch at time t on bus i (MW•h) in the s^{th} scenario.

The hourly LMP for each scenario is given by

$$\pi_{i,t}^s = \lambda_t^s + \sum_{l=1}^M GSF_{l-i} (\mu_{l,t}^{s,\min} - \mu_{l,t}^{s,\max}) \quad (6.12f)$$

Therefore, the net revenue of LSE can be formulated as (6.13a) and then transformed into (6.13b), while the constraints are modelled in (6.13c) to (6.13r).

$$\max R_n = \sum_{s=1}^S p_s \times \sum_{t=1}^{24} \left[\sum_{i \in A} (\eta_{i,t} - \pi_{i,t}^s) \times D_{i,t}^{s,0} + \pi_{i,t}^s \times S_{i,t} \right] \quad (6.13a)$$

$$\begin{aligned}
R_n = & \sum_{s=1}^S p_s \times \sum_{t=1}^{24} \left\{ \sum_{i \in A} (\eta_{i,t} - \pi_{i,t}^s) \times D_{i,t}^{s,0} + \lambda_t^s \times \left(\sum_{i \in SC} D_{i,t}^{s,0} + \sum_{i \notin SC} D_{i,t}^s \right) \right. \\
& + \sum_{l=1}^M \left[\mu_{l,t}^{s,\max} \times (-Limit_l - \sum_{i \in SC} GSF_{l-i} \times D_{i,t}^{s,0} - \sum_{i \notin SC} GSF_{l-i} \times D_{i,t}^s) \right] \\
& + \sum_{l=1}^M \left[\mu_{l,t}^{s,\min} \times (-Limit_l + \sum_{i \in SC} GSF_{l-i} \times D_{i,t}^{s,0} + \sum_{i \notin SC} GSF_{l-i} \times D_{i,t}^s) \right] \\
& + \sum_{i=1}^N \left[\omega_{i,t}^{s,\max} \times (-G_{i,t}^{\max}) + \omega_i^{s,\min} \times (G_{i,t}^{\min}) \right] - \sum_{i=1}^N c_{i,t} \times G_{i,t}^s \left. \right\} \\
& + \sum_{t=1}^{23} \sum_{i=1}^N \left[\xi_{i,t}^{s,\max} \times (-RR_i^{\max}) + \xi_{i,t}^{s,\min} \times RR_i^{\min} \right]
\end{aligned} \tag{6.13b}$$

$$s.t. \text{ Constraint (6.6b)} \tag{6.13c}$$

$$c_{i,t} = \lambda_t^s + \sum_{l=1}^M GSF_{l-i} \times (\mu_{l,t}^{s,\min} - \mu_{l,t}^{s,\max}) + \omega_{i,t}^{s,\min} - \omega_{i,t}^{s,\max} + \xi_{i,t}^{s,\max} - \xi_{i,t}^{s,\min}, \forall t = 1 \tag{6.13d}$$

$$\begin{aligned}
c_{i,t} = & \lambda_t^s + \sum_{l=1}^M GSF_{l-i} \times (\mu_{l,t}^{s,\min} - \mu_{l,t}^{s,\max}) + \omega_{i,t}^{s,\min} - \omega_{i,t}^{s,\max} \\
& + \xi_{i,t}^{s,\max} - \xi_{i,t}^{s,\min} + \xi_{i,t-1}^{s,\min} - \xi_{i,t-1}^{s,\max}, \forall t = 2, \dots, 23
\end{aligned} \tag{6.13e}$$

$$c_{i,t} = \lambda_t^s + \sum_{l=1}^M GSF_{l-i} \times (\mu_{l,t}^{s,\min} - \mu_{l,t}^{s,\max}) + \omega_{i,t}^{s,\min} - \omega_{i,t}^{s,\max} + \xi_{i,t-1}^{s,\min} - \xi_{i,t-1}^{s,\max}, \forall t = 24 \tag{6.13f}$$

$$0 \leq \mu_{l,t}^{s,\min} \leq M_{\mu}^{\min} \nu_{\mu,l,t}^{s,\min}, \forall t = 1, \dots, 24 \tag{6.13g}$$

$$0 \leq Limit_l + \sum_{i=1}^N GSF_{l-i} \times (G_{i,t}^s - D_{i,t}^s) \leq M_{\mu}^{\min} (1 - \nu_{\mu,l,t}^{s,\min}), \forall t = 1, \dots, 24 \tag{6.13h}$$

$$0 \leq \mu_{l,t}^{s,\max} \leq M_{\mu}^{\max} \nu_{\mu,l,t}^{s,\max}, \forall t = 1, \dots, 24 \tag{6.13i}$$

$$0 \leq Limit_l - \sum_{i=1}^N GSF_{l-i} \times (G_{i,t}^s - D_{i,t}^s) \leq M_{\mu}^{\max} (1 - \nu_{\mu,l,t}^{s,\max}), \forall t = 1, \dots, 24 \tag{6.13j}$$

$$0 \leq \omega_{i,t}^{s,\min} \leq M_{\omega}^{\min} \nu_{\omega,i,t}^{s,\min}, \forall t = 1, \dots, 24 \tag{6.13k}$$

$$0 \leq G_{i,t}^s - G_i^{\min} \leq M_{\omega}^{\min} (1 - \nu_{\omega,i,t}^{s,\min}), \forall t = 1, \dots, 24 \tag{6.13l}$$

$$0 \leq \omega_{i,t}^{s,\max} \leq M_{\omega}^{\max} v_{\omega,i,t}^{s,\max}, \forall t = 1, \dots, 24 \quad (6.13m)$$

$$0 \leq G_i^{\max} - G_{i,t}^s \leq M_{\omega}^{\max} (1 - v_{\omega,i,t}^{s,\max}), \forall t = 1, \dots, 24 \quad (6.13n)$$

$$0 \leq \xi_{i,t}^{s,\min} \leq M_{\xi}^{\min} v_{\xi,i,t}^{s,\min}, \forall t = 1, \dots, 23 \quad (6.13o)$$

$$0 \leq G_{i,t+1}^s - G_{i,t}^s - RR_i^{\min} \leq M_{\xi}^{\min} (1 - v_{\xi,i,t}^{s,\min}), \forall t = 1, \dots, 23 \quad (6.13p)$$

$$0 \leq \xi_{i,t}^{s,\max} \leq M_{\xi}^{\max} v_{\xi,i,t}^{s,\max}, \forall t = 1, \dots, 23 \quad (6.13q)$$

$$0 \leq RR_i^{\max} - G_{i,t+1}^s + G_{i,t}^s \leq M_{\xi}^{\max} (1 - v_{\xi,i,t}^{s,\max}), \forall t = 1, \dots, 23 \quad (6.13r)$$

6.4 Case Studies

In this section, the proposed strategic scheduling approach is applied to a modified PJM 5-bus system, which is chosen for its ability to illustrate the concept to the audience, as well as a modified IEEE 118-bus system to demonstrate the algorithm in a larger system. The simulation has been done in the General Algebraic Modeling System (GAMS), which has the capability to solve large-scale optimization problems.

6.4.1 PJM 5-bus System

The test system is modified from the PJM 5-bus system. The system parameters are from [26]. In this study, the peak load in this system is 780MW and the total load is equally distributed on buses B, C, and D. The system is depicted in Figure 6.2. Two small size generators on Bus A are the gas turbines which have the capability to start up quickly. The ramp rate for the other generators is 50% of the maximum power output [154].

In the case study, the LSE bidder with ES is located at bus D. The flat electricity rate offered to the customers at bus D by the LSE is set as \$21/MW h. The daily load curve is shown in Figure 6.3. This load curve is a typical double peak load curve with the higher peak in the

night. The forecast peak load follows the Normal distribution. Assume that the standard deviation σ is 5% of mean load u and five scenarios are chosen to represent to load uncertainty [155], [156]. The peak load of five scenarios are $[u-2\sigma, u-\sigma, u, u+\sigma, u+2\sigma]$ and the corresponding probability for each scenario is $[0.023, 0.135, 0.684, 0.135, 0.023]$. More details concerning the load forecast have been introduced in [94], though it is out of the research scope of this dissertation to discuss the pros and cons of various demand forecast methods.

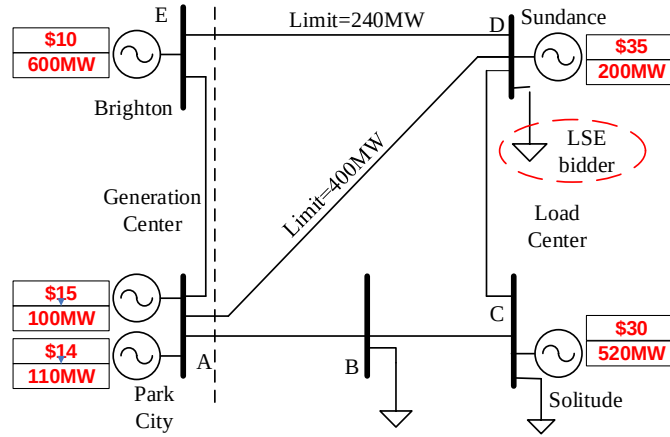


Figure 5.2 PJM 5-bus system and generation parameters

6.4.2 Comparison of Traditional Scheduling and Strategic Scheduling

In this subsection, the energy storage scheduling results from the traditional method in sub-section 2.2 and the strategic scheduling method proposed in this chapter will be compared. The parameters of energy storage system such as minimum/maximum storage status (E^{min}/E^{max}), initial storage capacity (E_0), charging/discharging factors (ζ_c/ζ_d), and maximum charging/discharging power ($P^{c(max)}/P^{d(max)}$) are listed in Table 1. In this table, the percentage is w.r.t. the total ES capacity. In this study, the LMP results obtained from ISO's ED under each

load scenario without ES are utilized as the forecast LMP for LSE in the ES traditional scheduling. The profits of the LSE in the ISO's day ahead market considering different ES capacity under the traditional method and proposed strategic method is shown in Figure 4.

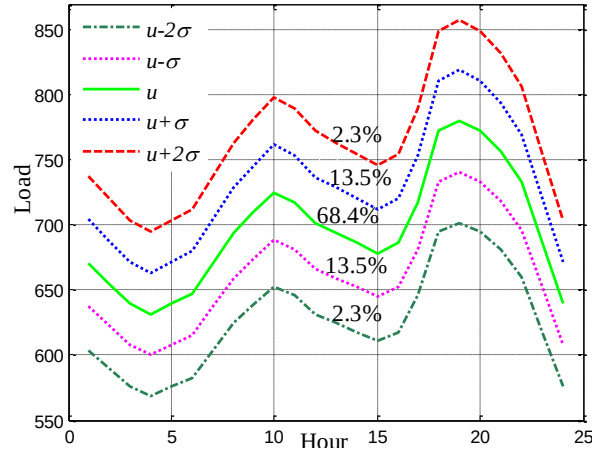


Figure 5.3 Daily load curve for PJM system on Nov 23, 2014

Table 6.1 Parameters of Energy Storage System

E^{min}	10%
E^{max}	90%
E_0	20%
ζ_c	0.9
ζ_d	0.9
$P^{c(max)}$	30%
$P^{d(max)}$	30%

Figure 6.4 shows that the profit increases linearly with the ES capacity in the traditional method. Using the strategic method proposed in this dissertation, the profit has a sharp change with the ES capacity. When the ES capacity is larger than a specified amount (10MW h in this case), the profit will increase significantly with the energy storage capacity. This is because, in

the traditional method, the impact of ES on the buses' LMPs is not considered. When the capacity of energy storage increases, the charging and discharging of LSE's ES will have the potential to change the bus load. Consequently, the bus LMPs will change due to the involvement of ES. Therefore, in the strategic method, the LSE can utilize this advantage to gain more profit.

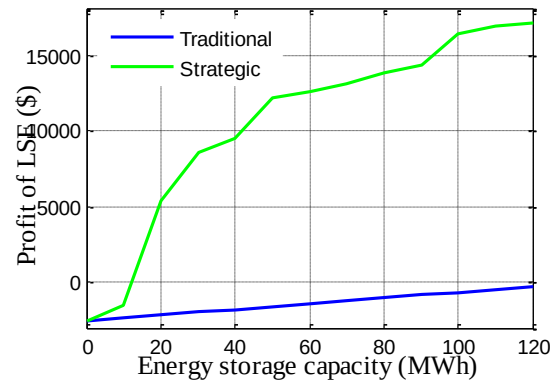


Figure 6.4 LSE's profit with different energy storage capacities under different scheduling methods

The impact of ES on the bus LMP is depicted in Figure 6.5, showing that the energy storage can reduce the LMP on peak hours when its capacity is large. For example, the LMPs during the peak hours in the morning from 9 AM to 11 AM are reduced significantly when the ES capacity is greater than 20 MW h. Also, during the peak hours in the evening from 19 PM to 22 PM, the duration of high LMPs is shortened with a larger ES capacity. In the real practice, the LSE should consider this impact on the day ahead scheduling of ES because the profit can change significantly between different scheduling methods of ES.

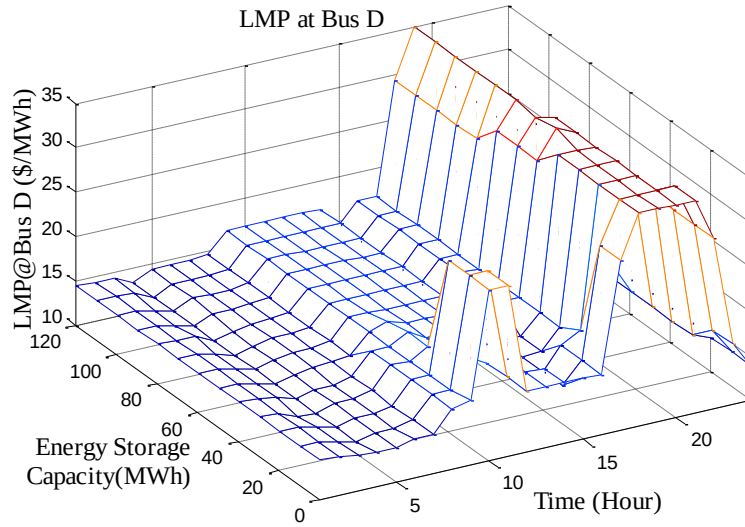


Figure 6.5 Daily LMP at Bus D under different energy storage capacities

Figure 6.6(a) is the capacity status of energy system under traditional method and the proposed strategic method. Figure 6.6(b) is the original LMP without ES and with ES under different bidding methods. In these figures, the capacity of energy storage in the system is 50 MW h. In Figure 6.6(a), the ES overall pattern of charging/discharging activities is similar between the traditional and strategic methods. The ES will charge during the off-peak hours and discharge during the peak hours. In the traditional method, this pattern is only decided by the daily load curve and the forecast LMP curve. In this method, the ES is prone to deep charging during off-peak hours and deep discharging during peak hours, although it maybe decrease the peak LMP as suggested by the results in the morning peak hours. However, the deep charging at 12 PM after the morning peak hours increases the LMP.

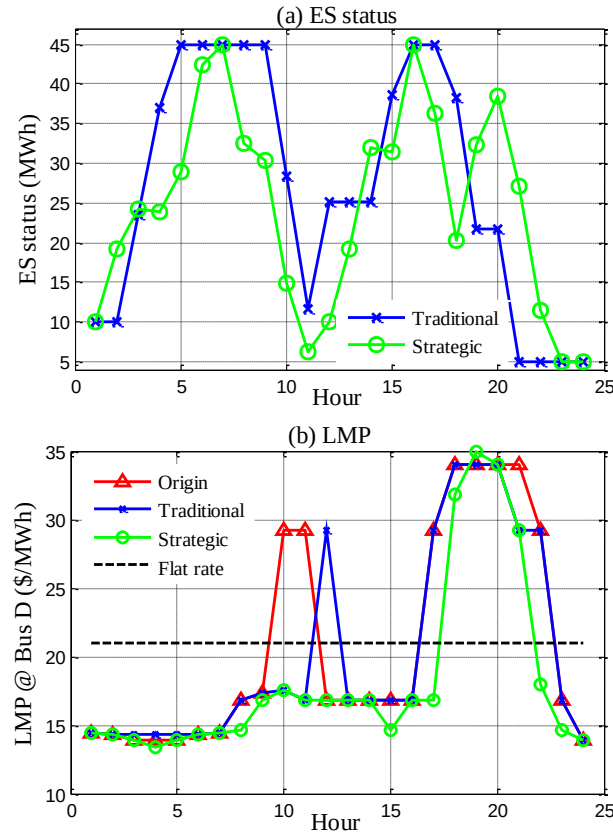


Figure 6.6 Daily energy storage status and LMP results under different methods

Discharging during the evening peak hours just reduces the LMP on 21 PM, and the LMP during the other peak hours does not change from the discharge of energy storage. Since the demand at the peak hours such as 18 PM to 20 PM is so high, the demand reduction through energy storage does not help reduce the LMP during these hours.

On the contrast, in the strategic methods, the impact of energy storage on the LMP is considered. Therefore, the energy storage will not deeply charge to increase the off-peak hours LMP, and it plays a more active role in reducing the LMP through discharging on the critical hours such as 17 PM to 18 PM, 21 PM to 23 PM. During these hours, the LMP can be reduced greatly through the ES discharging. Therefore, the ES discharges at these hours to reduce the

LMP during these hours. This is shown in Figure 6.6(b). During other peak hours (19 PM to 20 PM), it cannot reduce the LMP through the ES discharging. Therefore, in the strategic method, the ES will discharge at some critical hours to reduce the LMPs such that the capacity of energy storage is utilized in its most efficient way to help the LSE obtain more profit.

6.4.3 IEEE 118-bus System

The IEEE 118-bus system [3] is applied here to demonstrate the applicability of the proposed method to larger systems. The system is depicted in Figure 6.7. The generation data is listed in Table 6.2. The maximum ramp rate for each generator is set to 50% of its maximum power output [58]. Seven thermal limits are applied to the transmission system: 100 MW for line 1-3 and 6-7, 175 MW for line 3-12 and 46-47, 150 MW for lines 15-33, 300 MW for line 71-72 and 250 MW for line 70-75.

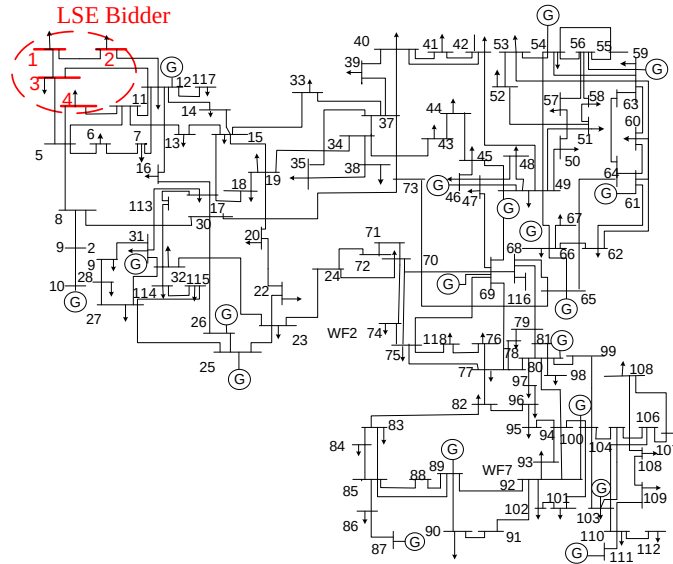


Figure 6.7 LSE bidder in IEEE 118-bus system integrated with two wind farms

The daily load curve is shown in Figure 6.8. This load curve is a typical double-peak load curve with the higher peak at noon. The forecast peak load follows the Gaussian distribution. Similar to the previous case study, we may assume that the standard deviation σ is 5% of mean load u and five scenarios are chosen to represent load uncertainty. The peak load of five scenarios is $[u-2\sigma, u-\sigma, u, u+\sigma, u+2\sigma]$ and the corresponding probability for each scenario is $[0.023, 0.135, 0.684, 0.135, 0.023]$.

The LSE performing the strategic bidding is located at the northwestern part of the system covering the demands on Bus 1, Bus 2, Bus 3 and Bus 4. LMP on Bus 1 to Bus 4 versus the system load level is shown in Figure 6.8. The average demand at each bus of this LSE and the corresponding flat electricity rates are shown in Table 6.3.

Four ES systems with 30 MW h, 10 MW h, 20 MW h and 20 MW h are installed on Bus 1 to Bus 4, respectively. The parameters of ES are the same as the previous study in Table 6.1. The results of the LSE bidder in DA market without and with ES are listed in Table 4. Figure 6.9 is the ES capacity status under traditional method and strategic method, and Figure 10 is the daily LMP under different methods.

In Table 6.4, it shows that, without ES, the net revenue of LSE is \$221.63 which is the same under different methods because the LSE has no capability to change its load curve without ES. Therefore, its net revenue is the same under different methods. After installing ES, the net revenue increases from \$575.72 to \$784.76 when the scheduling method changes from the traditional price-based method to the proposed strategic scheduling method.

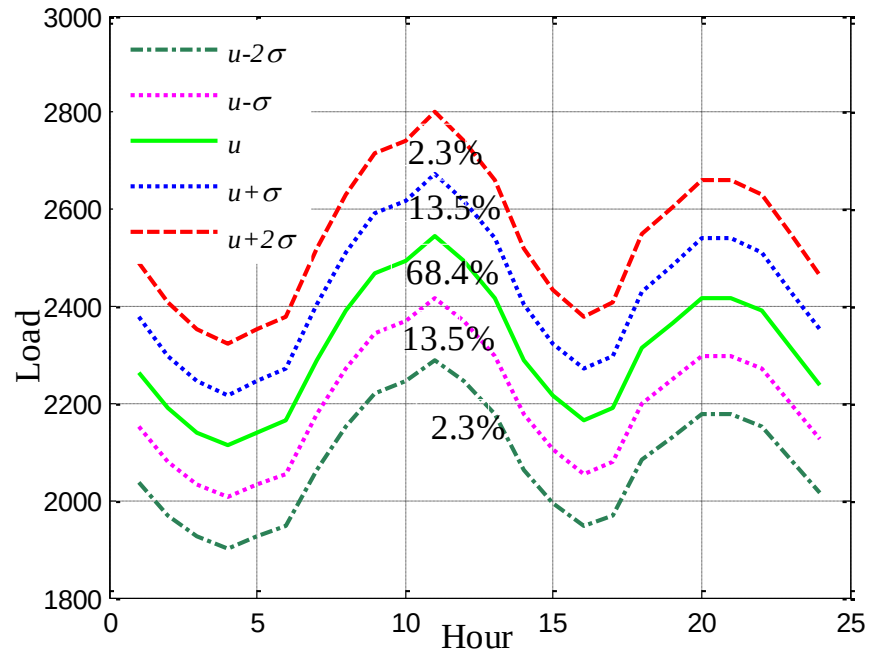


Figure 6.8 Daily load curve for IEEE 118-bus system

Table 6.2 Generation Parameters

Gen	Bus	Price (\$/MW·h)	Pmax (MW)	Gen	Bus	Price (\$/MW·h)	Pmax (MW)
1	10	5	550	11	65	60	491
2	12	7.5	185	12	66	65	492
3	25	10	320	13	69	70	805
4	26	12.5	414	14	80	80	577
5	31	30	107	15	87	90	104
6	46	35	119	16	89	100	707
7	49	40	304	17	100	110	352
8	54	45	148	18	103	120	140
9	59	50	255	19	111	130	136
10	61	55	260				

Similar to Figure 6.6(a) in the previous case study, the ES capacity curves under different scheduling methods shown in Figure 6.9 also demonstrate that the charging/discharging of ES under the traditional method is based on the daily load curve and the forecast LMP curve, and that the value of charging/discharging power is not time sensitive.

In the strategic method, the charging power of ES is not too large to increase the LMPs, and the discharging is chosen at the moments when it is effective to reduce the LMPs. This is shown in Figure 6.10. In the traditional method, the charging increases the LMP at 4 AM and 15 PM shown in Figure 6.10(b). In the strategic method, the LMPs at 7 AM, 14 PM and 12 AM are reduced through the ES discharging on Bus 1 to Bus 4.

Table 6.3 Bus Parameters of LSE bidder

Bu s	Base Load (MW)	Flat Electricity Rate
1	30.6	17.5
2	12.0	19.5
3	23.4	17.0
4	23.4	13.2

Table 6.4 Profit of LSE under different methods

Case	ES Capacity (Bus)	Profit (\$)	
		Traditional	Strategic
1	0	221.63	221.63
2	30 (1), 10(2), 20 (3), 20 (4)	575.72	784.76

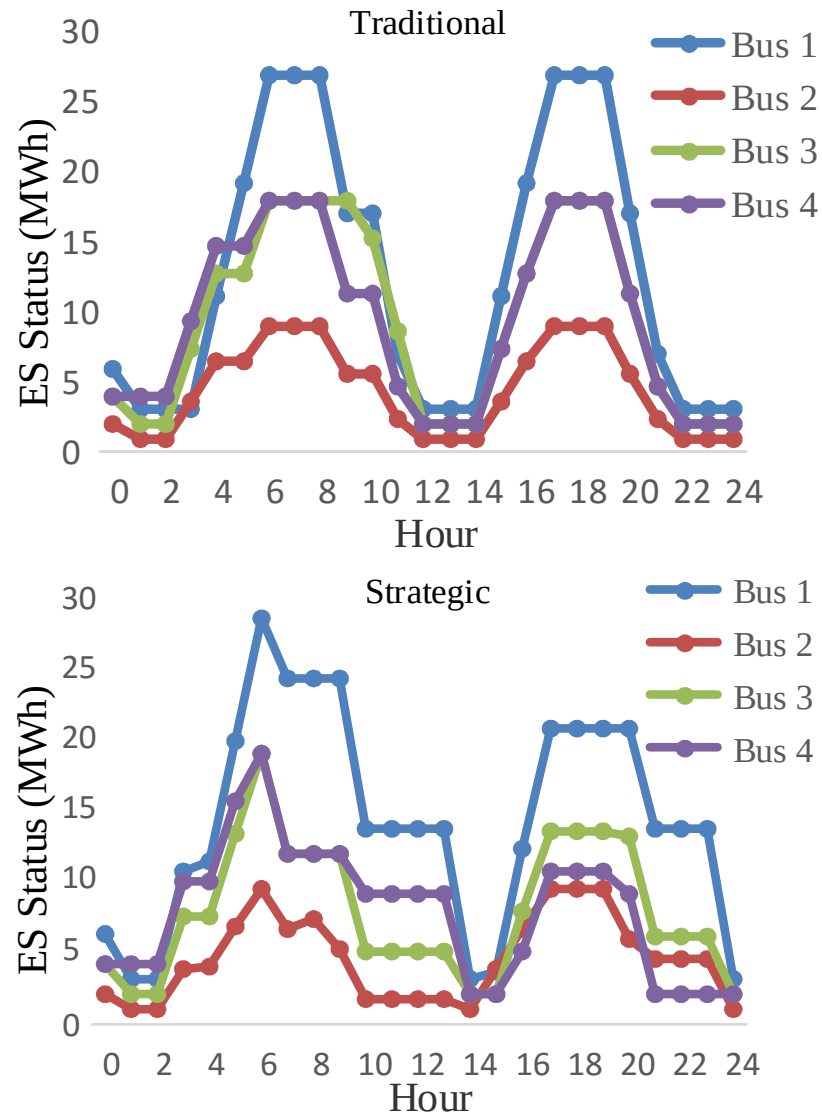


Figure 6.9 ES status under different scheduling methods

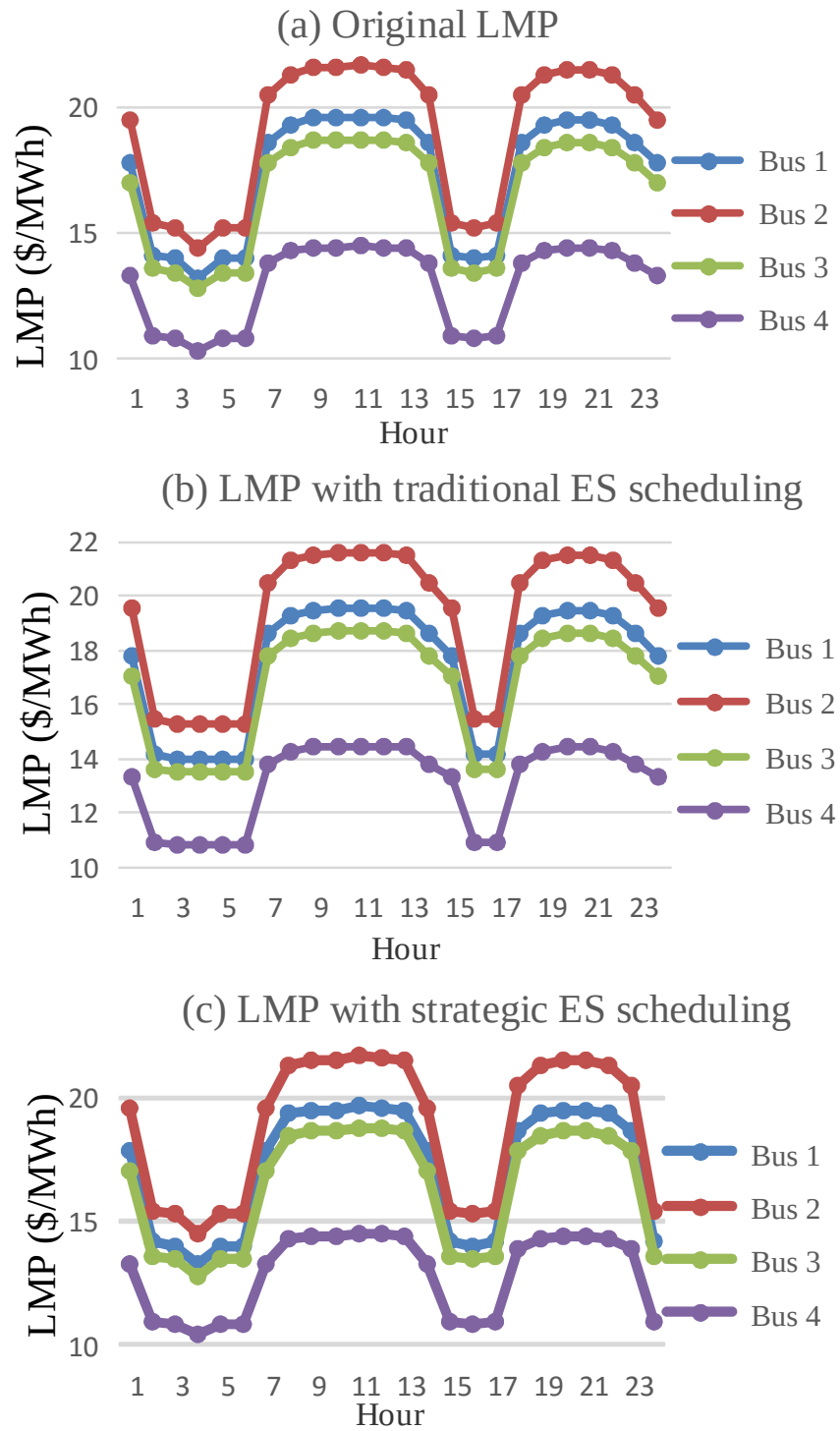


Figure 6.10 Daily load curve for IEEE 118-bus system

6.5 Conclusions

With the substantially increasing penetration of renewable generation such as wind power, the utilization of energy storage in power systems is expected to be an economic and effective means to mitigate the output uncertainty of renewable generation. Under this condition, the scheduling of energy storage (ES) owned by the LSE to maximize its profit has received a growing research interest. In this chapter, a strategic scheduling method of ES for LSE is proposed as a bi-level optimization model. Then, by recasting the lower-level problem into the KKT optimality condition, this bi-level problem is transformed to a single level MPEC problem, and further converted into an MILP problem which is easy to solve using available software tools. More profit of the LSE obtained from the DA market can be realized with this strategic scheduling method with ES. The impact of charging/discharging of ES on LMPs is endogenously considered in the proposed model. Therefore, charging of energy storage will not increase the LMP whereas the discharging will be chosen during some LMP-sensitive hours to decrease the LMP.

Future work may include the energy and ancillary service (AS) co-optimization model given that ES is also a viable and effective source to participate in the regulation and spinning reserve market. In addition, modeling Day-Ahead and Real-Time market clearing price dynamics is also necessary since it will affect the AS revenues of the ES owners during the settlement process.

CHAPTER 7

CONCLUSION

7.1 Main Contributions and Conclusion

This work consists of five main parts: 1) reactive power planning (RPP) considering high penetration of wind power; 2) location marginal price interval evaluation considering wind power uncertainty; 3) strategic bidding of LSE considering coupon based demand response (CBDR) and scheduling of energy storage in the LMP market; 4) the impact from financial transmission rights on LSE's CBDR programs; and 5) a bidding strategy for LSE-owned energy storages under CBDR programs.

In Chapter II, a voltage stability constrained reactive power planning (RPP) model considering high penetration of wind energy is proposed based on a stochastic multi-scenario VSCOPF framework to address wind uncertainty. Correlations among different wind plants as well as transmission N-1 contingency are modeled in the study. Traditional RPP problem has been re-defined as a two-stage optimization process that includes both the VAR compensation cost and the expected generation cost considering the impact of wind uncertainty. Benders' decomposition is applied to solve the stochastic two stage problem. Simulation results suggest that the total cost is a better optimization objective as opposed to only VAR cost in RPP with wind power integrated in power systems, and the correlation among wind farms impacts both VAR costs and generation costs. Thus, wind power generator's reactive power capability lends itself as an alternative resource to effectively facilitate the wind power incorporated RPP process with the proposed method.

In Chapter III, the locational marginal price (LMP) interval evaluation problem is formulated as a bi-level optimization problem with the LMP maximization or minimization as the upper one and the ISO's economic dispatch as the lower one. Then, the bi-level optimization model is solved with mathematical program with equilibrium constraints (MPEC) and mixed-integer linear programming (MILP). By the proposed approach, the LMP intervals can be obtained much faster than the conventional Monte Carlo Simulation method.

In Chapter IV, a strategic bidding model for LSE is proposed considering coupon-based demand response and wind power uncertainty. First, a strategic bidding model for LSEs using bi-level optimization for CBDR is proposed by recasting the lower-level problem into the KKT optimality condition. Thus, this bi-level problem is transformed to a MPEC problem, then further converted into a MILP problem which is easy to solve by available software tools. A probabilistic model of residential demand is applied to mimic customers' behavior patterns toward different coupon prices. Therefore, the time-consuming interacting process with numerous customers can be avoided, which makes online implementation of CBDR feasible. The strategic bidding is studied at five typical operating points representing different load levels. The simulation results demonstrate that change of expected net revenue (i.e., ΔENR) is closely related to the critical load level (CLL), because this determines whether there will be a considerable price change or not if the load is reduced. The wind power capacity does not change the patterns of ΔENR versus coupon prices, while the wind uncertainty may have an impact to ΔENR . ΔENR may either decrease with wind uncertainty when LMP is sensitive to load level or increase when LMP is not sensitive to load level.

In Chapter V, a strategic CBDR bidding approach for the LSE considering the impact of FTR and wind power is proposed. In this model, the uncertainty of wind power output and

customers' electricity consumption behavior patterns toward different coupon prices are also included. In this part, FTR's congestion compensation is modeled in the LSEs' strategic CBDR bidding process. This model utilizes a bi-level optimization which is transformed to a MPEC problem similar to the mathematical solution in Chapter IV. The impact of FTR on the strategic CBDR bidding of LSE is analyzed with different FTR paths. It demonstrates that FTR's influence on LSEs' strategic CBDR bidding results varies w.r.t. different FTR paths. The impact increases with the LMP differences between the injection and the delivery buses of FTRs' paths. With an increasing FTR amount, the coupon prices which the LSE offers to customers are prone to decrease if the FTR holding can impact the bidding results. Under this circumstance, the LSE's incentive to stimulate customers to reduce their demand is decreasing with its FTR holding amount. The simulation results demonstrate the benefit of the congestion compensation of FTR under high load level and the profit obtained from the LMP reduction through CBDR should be co-optimized. Also, LSEs can obtain higher profit by considering FTR in its bidding process.

In Chapter VI, the energy storage scheduling method for LSE is proposed. In this model, the load uncertainty is modeled as a set of probabilistic scenarios. A strategic scheduling method of ES for LSE is proposed as a bi-level optimization model. Then, by recasting the lower-level problem into the KKT optimality condition, this bi-level problem is transformed to a single level MPEC problem, and further converted into an MILP problem which is easy to solve using available software tools. More profit of the LSE obtained from the DA market can be realized with this strategic scheduling method with ES. The impact of charging and discharging of ES on LMPs is endogenously considered in the proposed model. Therefore, charging of energy storage will not increase the LMP whereas the discharging will be chosen during some LMP-sensitive

hours to decrease the LMP.

7.2 Future Research Work

Major challenges arise from the intermittent nature of wind power and the “non-dispatchability” of wind resources in electric power market operations. The utilization of energy storage (ES) technologies to increase operational flexibility is commonly regarded as a logical complement for the systems with high-penetration wind power. Therefore, regulators and policy makers have started to investigate the impact and benefit of ES integrated into the grid and initiated some pilot procurement mandate for load serving entities (LSEs) such as a utility company. As LSEs’ ES procurement becomes inevitable with increasing scale in the near future, there exists opportunities for LSE to better understand how to optimally schedule ES in order to either obtain more investment returns or reduce ratepayers’ cost.

Future work may include the energy and ancillary service (AS) co-optimization model given that ES is also a viable and effective source to participate in the regulation and spinning reserve market. In addition, modeling day-ahead and real-time market clearing price dynamics is also necessary since it will affect the AS revenues of the ES owners during the settlement process.

LIST OF REFERENCES

- [1] X. Fang, F. Li, Y. Wei, R. Azim, and Y. Xu, "Reactive power planning under high penetration of wind energy using Benders decomposition," *IET Gener. Transm. Distrib.*, vol. 9, no. 14, pp. 1835–1844, 2015.
- [2] P. Brown, "U.S. Renewable Electricity : How Does Wind Generation Impact Competitive Power Markets ?," 2012.
- [3] Y. Wei, F. Li, and K. Tomsovic, "Measuring the volatility of wholesale electricity prices caused by wind power uncertainty with a correlation model," *IET Renew. Power Gener.*, vol. 6, no. May, pp. 315–323, 2012.
- [4] F. Li and Y. Wei, "A probability-driven multilayer framework for scheduling intermittent renewable energy," *IEEE Trans. Sustain. Energy*, vol. 3, no. 3, pp. 455–464, 2012.
- [5] Z. Jin, F. Li, X. Ma, and S. Djouadi, "Semi-Definite Programming for Power Output Control in Wind Energy Conversion System," *IEEE Trans. Sustain. Energy*, vol. 5, no. 2, pp. 466–475, 2014.
- [6] C. Huang, F. Li, and Z. Jin, "Maximum Power Point Tracking Strategy for Large-Scale Wind Generation Systems Considering Wind Turbine Dynamics," *IEEE Trans. Ind. Electron.*, vol. 62, no. 4, pp. 2530–2539, 2015.
- [7] C. Huang, F. Li, T. Ding, Z. Jin, and X. Ma, "Second-order cone programming-based optimal control strategy for wind energy conversion systems over complete operating regions," *IEEE Trans. Sustain. Energy*, vol. 6, no. 1, pp. 263–271, 2015.
- [8] M. M. . Mahfouz and M. A. H. El-Sayed, "Static synchronous compensator sizing for

- enhancement of fault ride-through capability and voltage stabilisation of fixed speed wind farms,” *IET Renew. Power Gener.*, vol. 8, no. 1, pp. 1–9, 2014.
- [9] S. Zhang, K. J. Tseng, S. S. Choi, T. D. Nguyen, and D. L. Yao, “Advanced control of series voltage compensation to enhance wind turbine ride through,” *IEEE Trans. Power Electron.*, vol. 27, no. 2, pp. 763–772, 2012.
- [10] W. T. Liu, Y. K. Wu, C. Y. Lee, and C. R. Chen, “Effect of low-voltage-ride-through technologies on the first Taiwan offshore wind farm planning,” *IEEE Trans. Sustain. Energy*, vol. 2, no. 1, pp. 78–86, 2011.
- [11] Y. Xu, F. Li, Z. Jin, and C. Huang, “Flatness-based adaptive control (FBAC) for STATCOM,” *Electr. Power Syst. Res.*, vol. 122, pp. 76–85, 2015.
- [12] K. Ben-Kilani and M. Elleuch, “Structural analysis of voltage stability in power systems integrating wind power,” *IEEE Trans. Power Syst.*, vol. 28, no. 4, pp. 3785–3794, 2013.
- [13] Y.-Y. Hong and K.-L. Pen, “Optimal VAR Planning Considering Intermittent Wind Power Using Markov Model and Quantum Evolutionary Algorithm,” *IEEE Trans. Power Deliv.*, vol. 25, no. 4, pp. 2987–2996, 2010.
- [14] R. Míguez, F. Milano, R. Zárate-Miñano, and A. J. Conejo, “Optimal network placement of SVC devices,” *IEEE Trans. Power Syst.*, vol. 22, no. 4, pp. 1851–1860, 2007.
- [15] E. Vaahedi, Y. Mansour, C. Fuchs, S. Granville, S. Member, M. D. L. Latore, and H. Hamadanizadeh, “Dynamic Security Constrained Optimal Power Flow/VAr Planning,” *IEEE Trans. Power Syst.*, vol. 16, no. 1, pp. 38–43, 2001.

- [16] R. Mahanty and P. Gupta, "Reactive optimal power flow incorporating margin enhancement constraints with nonlinear interior point method," *IEE Proc.-Gener., Transm. Distrib.*, vol. 152, no. 6, pp. 961–968, 2005.
- [17] X. Fang, F. Li, and Y. Xu, "Reactive Power Planning Considering High Penetration of Wind Energy," in *IEEE PES T&D Conference and Exposition*, 2014, pp. 1–5.
- [18] W. Zhang, F. Li, and L. M. Tolbert, "Voltage stability constrained optimal power flow (VSCOPF) with two sets of variables (TSV) for reactive power planning," *2008 IEEE PES T&D Conf. Expo.*, pp. 1–6, 2008.
- [19] Y. Wang, S. Member, F. Li, S. Member, Q. Wan, and H. Chen, "Reactive Power Planning Based on Fuzzy Clustering , Gray Code , and Simulated Annealing," *IEEE Trans. Power Syst.*, vol. 26, no. 4, pp. 2246–2255, 2011.
- [20] Y.-T. Hsiao, C.-C. Liu, H.-D. Chiang, and Y.-L. Chen, "A new approach for optimal VAr sources planning in large scale electric power systems," *IEEE Trans. Power Syst.*, vol. 8, no. 3, pp. 988–996, 1993.
- [21] T. Gomez, I. J. Perez-Arriaga, J. Lumbreras, and V. M. Parra, "A security-constrained decomposition approach to optimal reactive power planning," *IEEE Trans. Power Syst.*, vol. 6, no. 3, pp. 1069–1076, 1991.
- [22] B. Cova, N. Losignore, P. Marannino, and M. Montagna, "Contingency Constrained Optimal Reactive Power Flow Procedures For voltage control in planning and operation," *IEEE Trans. Power Syst.*, vol. 10, no. 2, pp. 602–608, 1995.

- [23] R. J. Avalos, C. A. Canizares, F. Milano, and A. J. Conejo, "Equivalency of continuation and optimization methods to determine saddle-node and limit-induced bifurcations in power systems," *IEEE Trans. Circuits Syst. I Regul. Pap.*, vol. 56, no. 1, pp. 210–223, 2009.
- [24] A. Rabiee and M. Parniani, "Voltage security constrained multi-period optimal reactive power flow using benders and optimality condition decompositions," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 696–708, 2013.
- [25] C. S. Chang and J. S. Huang, "Optimal multiobjective SVC planning for voltage stability enhancement," *IEE Proc.-Gener., Transm. Distrib.*, vol. 145, no. 2, pp. 203–209, 1998.
- [26] W. Zhang, F. Li, and L. M. Tolbert, "Review of reactive power planning: Objectives, constraints, and algorithms," *IEEE Trans. Power Syst.*, vol. 22, no. 4, pp. 2177–2186, 2007.
- [27] L. Baringo and A. J. Conejo, "Wind power investment: A Benders decomposition approach," *IEEE Trans. Power Syst.*, vol. 27, no. 1, pp. 433–441, 2012.
- [28] D. Villanueva, A. Feijóo, and J. L. Pazos, "Simulation of correlated wind speed data for economic dispatch evaluation," *IEEE Trans. Sustain. Energy*, vol. 3, no. 1, pp. 142–149, 2012.
- [29] Y. Gao and R. Billinton, "Adequacy assessment of generating systems containing wind power considering wind speed correlation," *IET Renew. Power Gener.*, vol. 1, no. 1, pp. 10–16, 2007.

- [30] S. Engelhardt, I. Erlich, C. Feltes, J. Kretschmann, and F. Shewarega, "Reactive power capability of wind turbines based on doubly fed induction generators," *IEEE Trans. Energy Convers.*, vol. 26, no. 1, pp. 364–372, 2011.
- [31] A. Ahmidi, X. Guillaud, Y. Besanger, and R. Blanc, "A multilevel approach for optimal participating of wind farms at reactive power balancing in transmission power system," *IEEE Syst. J.*, vol. 6, no. 2, pp. 260–269, 2012.
- [32] S. Foster, L. Xu, and B. Fox, "Coordinated reactive power control for facilitating fault ride through of doubly fed induction generator- and fixed speed induction generator-based wind farms," *IET Renew. Power Gener.*, vol. 4, no. 2, p. 128, 2010.
- [33] T. Lund, P. Sorensen, and J. Eek, "Reactive power capability of a wind turbine with doubly fed induction generator," *Wind Energy*, vol. 10, pp. 379–394, 2007.
- [34] L. L. Freris, *Wind Energy Conversion Systems*. Prentice Hall, 1990.
- [35] X. Fang, F. Li, N. Gao, and Q. Guo, "Available Transfer Capability of Photovoltaic Generation Incorporated System," in *IEEE PES General Meeting*, 2014, pp. 1–5.
- [36] X. Fang, Q. Guo, D. Zhang, and S. Liang, "Capacity credit evaluation of photovoltaic generation based on system reserve capacity," in *IEEE Asia-Pacific Power and Energy Engineering Conference (APPEEC)*, 2012, pp. 1–4.
- [37] R. Torquato, Q. Shi, W. Xu, and W. Freitas, "A Monte Carlo simulation platform for studying low voltage residential networks," *IEEE Trans. Smart Grid*, vol. 5, no. 6, pp. 2766–2776, 2014.

- [38] Vestas, “General Specification V90 - 3.0 MW,” 2004. [Online]. Available: http://www.gov.pe.ca/photos/sites/envengfor/file/950010R1_V90-GeneralSpecification.pdf.
- [39] B. Hasche, A. Keane, and M. O’Malley, “Capacity value of wind power, calculation, and data requirements: The Irish power system case,” *IEEE Trans. Power Syst.*, vol. 26, no. 1, pp. 420–430, 2011.
- [40] H. Yuan, X. Li, F. Li, X. Fang, H. Cui, and Q. Hu, “Mitigate Overestimation of Voltage Stability Margin by Coupled Single-Port Circuit Models,” in *IEEE PES General Meeting*, 2016, pp. 1–5.
- [41] J. C. López, J. Contreras, J. I. Munoz, and J. R. S. Mantovani, “A Multi-Stage Stochastic Non-Linear Model for Reactive Power Planning Under Contingencies,” *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 1503–1514, 2013.
- [42] W. D. Rosehart, C. A. Canizares, and V. H. Quintana, “Effect of detailed power system models in traditional and voltage-stability-constrained optimal power-flow problems,” *IEEE Trans. Power Syst.*, vol. 18, no. 1, pp. 27–35, 2003.
- [43] F. Hu, K. Sun, A. Del Rosso, E. Farantatos, and N. Bhatt, “Measurement-Based Real-Time Voltage Stability Monitoring for Load Areas,” *IEEE Trans. Power Syst.*, pp. 1–12, 2016.
- [44] F. Hu, K. Sun, A. Del Rosso, E. Farantatos, and N. Bhatt, “An adaptive three-bus power system equivalent for estimating voltage stability margin from synchronized phasor

- measurements,” in *IEEE PES General Meeting*, 2014, pp. 1–5.
- [45] X. Fang, F. Li, Q. Hu, and N. Gao, “System Load Margin Evaluation using Mixed-Integer Conic Optimization,” in *North America Power Symposium (NAPS)*, 2015, pp. 1–5.
- [46] C. A. Canizares, “Voltage Stability Assessment: Concepts, Practices and Tools,” 2002.
- [47] H. Yuan and F. Li, “Hybrid voltage stability assessment (VSA) for N - 1 contingency,” *Electr. Power Syst. Res.*, vol. 122, pp. 65–75, 2015.
- [48] M. Eghbal, N. Yorino, E. E. El-Araby, and Y. Zoka, “Multi-load level reactive power planning considering slow and fast VAR devices by means of particle swarm optimisation,” *IET Gener., Transm. Distrib.*, vol. 1, no. 2, p. 324, 2007.
- [49] N. Gröwe-Kuska, H. Heitsch, and W. Römisch, “Scenario reduction and scenario tree construction for power management problems,” *Proc. 2003 IEEE Bol. PowerTech Conf.*, vol. 3, pp. 152–158, 2003.
- [50] Y. H. Choi, S. Seo, S. Kang, and B. Lee, “Justification of effective reactive power reserves with respect to a particular bus using linear sensitivity,” *IEEE Trans. Power Syst.*, vol. 26, no. 4, pp. 2118–2124, 2011.
- [51] W. Ju, J. Qi, and K. Sun, “Simulation and analysis of cascading failures on an NPCC power system test bed,” in *IEEE PES General Meeting*, 2015, pp. 1–5.
- [52] J. Qi, W. Ju, and K. Sun, “Estimating the Propagation of Interdependent Cascading Outages with Multi-Type Branching Processes,” *IEEE Trans. Power Syst.*, pp. 1–10,

2016.

- [53] S. Greene, I. Dobson, and F. L. Alvarado, "Contingency ranking for voltage collapse via sensitivities from a single nose curve," *IEEE Trans. Power Syst.*, vol. 14, no. 1, pp. 232–240, 1999.
- [54] R. E. Rosenthal, "GAMS — A User ' s Guide," no. January, 2016.
- [55] "Power System Test Case Archive." [Online]. Available: <http://www.ee.washington.edu/research/pstca/>.
- [56] M. Bolinger and R. Wiser, "Wind power price trends in the United States: Struggling to remain competitive in the face of strong growth," *Energy Policy*, vol. 37, no. 3, pp. 1061–1071, 2009.
- [57] J. Widén, "Correlations between large-scale solar and wind power in a future scenario for Sweden," *IEEE Trans. Sustain. Energy*, vol. 2, no. 2, pp. 177–184, 2011.
- [58] "IEEE 118-bus System." [Online]. Available: motor.ece.iit.edu/data/IEAS_IEEE118.doc.
- [59] S. Granville, M. V. F. Pereira, and A. Monticelli, "An integrated methodology for var sources planning," *IEEE Trans. Power Syst.*, vol. 3, no. 2, pp. 549–557, 1988.
- [60] F. Li and R. Bo, "Congestion and Price Prediction," *IEEE Trans. Power Syst.*, vol. 24, no. 2, pp. 911–922, 2009.
- [61] C. Boonchuay, "Improving regulation service based on adaptive load frequency control in LMP energy market," *IEEE Trans. Power Syst.*, vol. 29, no. 2, pp. 988–989, 2014.

- [62] S. J. Kazempour, A. J. Conejo, and C. Ruiz, “Strategic generation investment using a complementarity approach,” *IEEE Trans. Power Syst.*, vol. 26, no. 2, pp. 940–948, 2011.
- [63] B. Wang, X. Fang, X. Zhao, and H. Chen, “Bi-level optimization for available transfer capability evaluation in deregulated electricity market,” *Energies*, vol. 8, no. 12, pp. 13344–13360, 2015.
- [64] J. Fortuny-Amat and B. McCarl, “A Representation and Economic Interpretation of a Two-Level Programming Problem,” *J. Oper. Res. Soc.*, vol. 32, no. 9, pp. 783–792, 1981.
- [65] D. S. Kirschen, “Demand-side view of electricity markets,” *IEEE Trans. Power Syst.*, vol. 18, no. 2, pp. 520–527, 2003.
- [66] “National Action Plan on Demand Response,” *FERC*, 2010. [Online]. Available: <http://www.ferc.gov/legal/staff-reports/06-17-10-demand-response.pdf>.
- [67] L. Bai, F. Li, H. Cui, T. Jiang, H. Sun, and J. Zhu, “Interval optimization based operating strategy for gas-electricity integrated energy systems considering demand response and wind uncertainty,” *Appl. Energy*, 2015.
- [68] H. Huang, F. Li, and Y. Mishra, “Modeling Dynamic Demand Response Using Monte Carlo Simulation and Interval Mathematics for Boundary Estimation,” *IEEE Trans. Smart Grid*, vol. 6, no. 6, pp. 2704–2713, 2015.
- [69] “Benefits of Demand Response in Electricity Markets and Recommendations for Achieving Them,” *U.S. Department of Energy*, 2006. [Online]. Available: [file:///C:/Users/SATELLITE/Google Drive/Referencias Doctorado/U.S. Department of](file:///C:/Users/SATELLITE/Google%20Drive/Referencias%20Doctorado/U.S.%20Department%20of%20Energy/Benefits%20of%20Demand%20Response%20in%20Electricity%20Markets%20and%20Recommendations%20for%20Achieving%20Them.pdf)

Energy (DOE) - 2006 - Benefits of Demand Response in Electricity Markets and Recommendations for Achieving Them.pdf.

- [70] R. Herranz, A. Muñoz San Roque, J. Villar, and F. A. Campos, “Optimal demand-side bidding strategies in electricity spot markets,” *IEEE Trans. Power Syst.*, vol. 27, no. 3, pp. 1204–1213, 2012.
- [71] M. Bilton, C. Ramsay, M. Leach, H. Devine-Wright, P. Devine-Wright, and D. Kirschen, “Domestic electricity consumption and demand side participation: opportunities and challenges for the UK power system,” in *Delivering a low carbon electricity system: technologies, economics and policy*, Cambridge University, 2008.
- [72] M. Pipattanasomporn, M. Kuzlu, S. Rahman, S. Member, M. Kuzlu, and S. Rahman, “An Algorithm for Intelligent Home Energy Management and Demand Response Analysis,” *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1–8, 2012.
- [73] R. L. Earle, “Demand elasticity in the california power exchange day-ahead market,” *Electr. J.*, vol. 13, no. 8, pp. 59–65, 2000.
- [74] C. Goldman, N. Hopper, R. Bhavirkar, B. Neenan, D. Boisvert, P. Cappers, D. Pratt, and K. Butkins, “Customer Strategies for Responding to Day-Ahead Market Hourly Electricity Pricing,” *Lawrence Berkeley National Laboratory*, 2005. [Online]. Available: <http://escholarship.org/uc/item/72x4824m.pdf>.
- [75] R. de Sa Ferreira, L. A. Barroso, P. R. Lino, M. M. Carvalho, and P. Valenzuela, “Time-of-use tariff design under uncertainty in price-elasticities of electricity demand: A

- stochastic optimization approach,” *IEEE Trans. Smart Grid*, vol. 4, no. 4, pp. 2285–2295, 2013.
- [76] S. Borenstein, J. Bushnell, and F. Wolak, “Measuring Market Inefficiencies in California’s Restructured Wholesale Electricity Market,” *Am. Econ. Rev.*, vol. 92, no. 5, pp. 1376–1405, 2002.
- [77] Youngsun Baek, S. W. Hadley, R. Uria-Martinez, G. Oladosu, A. M. Smith, F. Li, P. N. Leiby, and R. Lee, “Eastern Interconnection Demand Response Potential,” *Oak Ridge National Laboratory*, 2012. [Online]. Available: <http://info.ornl.gov/sites/publications/files/Pub37931.pdf>.
- [78] C. K. Woo, H. Liu, F. Kahrl, N. Schlag, J. Moore, and A. Olson, “Assessing the Economic Value of Transmission in Alberta’s Restructured Electricity Market,” *Electr. J.*, vol. 25, no. 3, pp. 68–80, 2012.
- [79] C. King and S. Chatterjee, “Predicting California Demand Response: How do Customers React to Hourly Prices?,” *Public Util. Fortn.*, pp. 27–32, 2003.
- [80] D. S. Kirschen, G. Strbac, P. Cumperayot, and D. P. De Mendes, “Factoring the elasticity of demand in electricity prices,” *IEEE Trans. Power Syst.*, vol. 15, no. 2, pp. 612–617, 2000.
- [81] H. Zhong, L. Xie, and Q. Xia, “Coupon incentive-based demand response: Theory and case study,” *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 1266–1276, 2013.
- [82] H. Yuan, F. Li, and Y. Wei, “LMP Step Pattern Detection based on Real-Time Data,”

- IEEE PES Gen. Meet.*, pp. 1–5, 2013.
- [83] A. L. Ott, “Experience with PJM market operation, system design, and implementation,” *IEEE Trans. Power Syst.*, vol. 18, no. 2, pp. 528–534, 2003.
- [84] D. He, J. Guo, and W. Lin, “The impact of trading wind power in both energy and regulation reserve market on system operation,” in *2012 North American Power Symposium, NAPS 2012*, 2012, pp. 1–5.
- [85] J. Guo, Y. Zhang, M. A. Young, M. J. Till, A. Dimitrovski, Y. Liu, P. Williging, and Y. Liu, “Design and Implementation of a Real-Time Off-Grid Operation Detection Tool from a Wide-Area Measurements Perspective,” *IEEE Trans. Smart Grid*, vol. 6, no. 4, pp. 2080–2087, 2014.
- [86] J. Guo, Y. Zhang, Y. Liu, M. Young, P. Irminger, A. Dimitrovski, and P. Willging, “Design and implementation of real-time off-grid detection tool based on FNET/GridEye,” in *2014 IEEE PES General Meeting*, 2014, pp. 1–5.
- [87] Department of Market Monitoring (CAISO), “Annual Report on Market Issues and Performance,” 2011.
- [88] X. Guan, Y. Ho, and F. Lai, “An Ordinal Optimization-Based Bidding Strategy for Electric Power Suppliers in the Daily Energy Market,” *IEEE Power Eng. Rev.*, vol. 21, no. 9, pp. 64–64, 2001.
- [89] H. Cui, F. Li, Q. Hu, L. Bai, and X. Fang, “Day-ahead coordinated operation of utility-scale electricity and natural gas networks considering demand response based virtual

- power plants,” *Appl. Energy*, vol. 176, no. 15, pp. 183–195, 2016.
- [90] F. Li and R. Bo, “DCOPF-based LMP simulation: Algorithm, comparison with ACOPF, and sensitivity,” *IEEE Trans. Power Syst.*, vol. 22, no. 4, pp. 1475–1485, 2007.
- [91] L. Baringo and A. J. Conejo, “Strategic offering for a wind power producer,” *IEEE Trans. Power Syst.*, vol. 28, no. 4, pp. 4645–4654, 2013.
- [92] L. Freeman, “A market simulation program for the standard market design and generation/transmission planning,” *IEEE PES Gen. Meet.*, pp. 442–446, 2003.
- [93] H. po Chao, “Demand response in wholesale electricity markets: The choice of customer baseline,” *J. Regul. Econ.*, vol. 39, no. 1, pp. 68–88, 2011.
- [94] G. Gross and F. D. Galiana, “Short-term load forecasting,” *Proc. IEEE*, vol. 75, no. 12, pp. 1558–1573, 1987.
- [95] “Demand Response Programs,” *Southern California Edison*. [Online]. Available: https://www.sce.com/wps/portal/home/business/savings-incentives/demand-response/!ut/p/b1/hc9Lj4IwFAXg3-KCpfRYfKC7-giU6CBiELsxYLCsIDWlQ_z3UydunDh6d-fmO8m9RJCYiDL5zmVS56pMinsW_V3HdpjLQ3CsphPw8dBIC39KJ5xqsNUA_wzDp_6GiGdiz6OBJk4YRMslrIe_wFkNKLgXzeb-uEPRpQ8wdD.
- [96] EnerNOC, “The Demand Response Baseline,” pp. 1–15, 2008.
- [97] “RESIDENTIAL ENERGY CONSUMPTION SURVEY (RECS).” [Online]. Available:

<http://www.eia.gov/consumption/residential/>.

- [98] “American Time Use Survey.” [Online]. Available: <http://www.bls.gov/tus/>.
- [99] “Center for Ultra-wide-area Resilient Electric Energy Transmission Networks.” [Online]. Available: <http://curent.utk.edu/>.
- [100] M. Buhrmester, T. Kwang, and S. D. Gosling, “Amazon’s Mechanical Turk: A new source of inexpensive, yet high-quality, data?,” *Perspect. Psychol. Sci.*, vol. 6, no. 1, pp. 3–5, 2011.
- [101] F. Li, “Continuous locational marginal pricing (CLMP),” *IEEE Trans. Power Syst.*, vol. 22, no. 4, pp. 1638–1646, 2007.
- [102] B. F. Hobbs, C. B. Metzler, and J.-S. Pang, “Strategic Gaming Analysis for Electric Power Systems: An MPEC Approach,” *IEEE Trans. Power Syst.*, vol. 21, no. 1, pp. 143–152, 2006.
- [103] S. Wogrin, E. Centeno, and J. Barquin, “Generation capacity expansion in liberalized electricity markets: A stochastic MPEC approach,” *IEEE Trans. Power Syst.*, vol. 26, no. 4, pp. 2526–2532, 2011.
- [104] L. Baringo and A. J. Conejo, “Transmission and wind power investment,” *IEEE Trans. Power Syst.*, vol. 27, no. 2, pp. 885–893, 2012.
- [105] S. J. Kazempour, A. J. Conejo, and C. Ruiz, “Strategic Generation Investment Considering Futures and Spot Markets,” *IEEE Trans. Power Syst.*, vol. 27, no. 3, pp.

1467–1476, 2012.

- [106] C. Ruiz, A. J. Conejo, and Y. Smeers, “Equilibria in an oligopolistic electricity pool with stepwise offer curves,” *IEEE Trans. Power Syst.*, vol. 27, no. 2, pp. 752–761, 2012.
- [107] “PJM Training Materials—LMP101.” [Online]. Available: <http://www.pjm.com/training/training-material.aspx>.
- [108] “GAMS.” [Online]. Available: <http://www.gams.com/>.
- [109] Y. Xu, Q. Hu, and F. Li, “Probabilistic model of payment cost minimization considering wind power and its uncertainty,” *IEEE Trans. Sustain. Energy*, vol. 4, no. 3, pp. 716–724, 2013.
- [110] “PJM Manual: Financial Transmission Rights.” [Online]. Available: <http://www.pjm.com/~media/documents/manuals/m06.ashx>.
- [111] X. Fang, F. Li, Q. Hu, and Y. Wei, “Strategic CBDR Bidding Considering FTR and Wind Power,” *IET Gener., Transm. Distrib.*, vol. 10, no. 10, pp. 2464–2474, 2016.
- [112] D. Apostolopoulou, G. Gross, and T. Güler, “Optimized FTR portfolio construction based on the identification of congested network elements,” *IEEE Trans. Power Syst.*, vol. 28, no. 4, pp. 4968–4978, 2013.
- [113] X. Fang, Q. Guo, D. Zhang, and S. Liang, “Capacity Credit Evaluation of Grid-connected Photovoltaic Generation Considering Weather Uncertainty,” *Autom. Electr. Power Syst.*, vol. 36, no. 10, pp. 27–32, 2012.

- [114] X. Fang, Q. Guo, D. Zhang, and S. Liang, "Capacity Credit Evaluation of Grid-Connected Photovoltaic Generation," *Power Syst. Technol.*, vol. 36, no. 9, pp. 31–35, 2012.
- [115] C. Babayiğit, P. Rocha, and T. K. Das, "A two-tier matrix game approach for obtaining joint bidding strategies in FTR and energy markets," *IEEE Trans. Power Syst.*, vol. 25, no. 3, pp. 1211–1219, 2010.
- [116] M. Klobasa, "Analysis of demand response and wind integration in Germany's electricity market," *IET Renew. Power Gener.*, vol. 4, no. 1, pp. 55–63, 2010.
- [117] A. J. Roscoe and G. W. Ault, "Supporting high penetrations of renewable generation via implementation of real-time electricity pricing and demand response," *IET Renew. Power Gener.*, vol. 4, no. 4, pp. 369–382, 2010.
- [118] M. A. Fotouhi Ghazvini, J. Soares, N. Horta, R. Neves, R. Castro, and Z. Vale, "A multi-objective model for scheduling of short-term incentive-based demand response programs offered by electricity retailers," *Appl. Energy*, vol. 151, pp. 102–118, 2015.
- [119] H. Wu, A. Al-Abdulwahab, and M. Shahidehpour, "Hourly demand response in day-ahead scheduling for managing the variability of renewable energy," *IET Gener. Transm. Distrib.*, vol. 7, no. 3, pp. 226–234, 2013.
- [120] L. Wu, "Impact of price-based demand response on market clearing and locational marginal prices," *IET Gener. Transm. Distrib.*, vol. 7, no. 10, pp. 1087–1095, 2013.
- [121] X. Fang, Y. Wei, and F. Li, "Evaluation of LMP Intervals Considering Wind Uncertainty," *IEEE Trans. Power Syst.*, vol. 31, no. 3, pp. 2495–2496, 2016.

- [122] K. Zare, S. Nojavan, and B. Mohammadi-Ivatloo, "Optimal bidding strategy of electricity retailers using robust optimisation approach considering time-of-use rate demand response programs under market price uncertainties," *IET Gener. Transm. Distrib.*, vol. 9, no. 4, pp. 328–338, 2015.
- [123] P. Grünewald, E. McKenna, and M. Thomson, "Going with the wind: temporal characteristics of potential wind curtailment in Ireland in 2020 and opportunities for demand response," *IET Renew. Power Gener.*, vol. 9, no. 1, pp. 66–77, 2015.
- [124] X. Fang, Q. Hu, F. Li, B. Wang, and Y. Li, "Coupon-Based Demand Response Considering Wind Power Uncertainty: A Strategic Bidding Model for Load Serving Entities," *IEEE Trans. Power Syst.*, vol. 31, no. 2, pp. 1025–1037, 2016.
- [125] B. Wang, N. Tang, X. Fang, S. Yang, and W. Ji, "A Multi Time Scales Reserve Rolling Revision Model of Power System With Large Scale Wind Power," *Proc. CSEE*, pp. 1–14, 2016.
- [126] J. Bastian, J. Zhu, V. Banunarayanan, and R. Mukerji, "Forecasting energy prices in a competitive market," *IEEE Comput. Appl. Power*, vol. 12, no. 3, pp. 40–45, 1999.
- [127] S. J. Kazempour and H. Zareipour, "Equilibria in an oligopolistic market with wind power production," *IEEE Trans. Power Syst.*, vol. 29, no. 2, pp. 686–697, 2014.
- [128] Q. Hu, X. Fang, F. Li, X. Xu, C. Chen, and H. Hu, "An Approach to Assess the Responsive Residential Demand to Financial Incentives," in *IEEE PES General Meeting*, 2015, pp. 1–5.

- [129] X. Fang, F. Li, Q. Hu, Y. Wei, and N. Gao, "The Impact of FTR on LSE 's Strategic Bidding Considering Coupon Based Demand Response," in *IEEE PES General Meeting*, 2015, pp. 1–5.
- [130] X. Fang, F. Li, Y. Wei, and H. Cui, "Strategic scheduling of energy storage for load serving entities in locational marginal pricing market," *IET Gener., Transm. Distrib.*, vol. 10, no. 5, pp. 1258–1267, 2016.
- [131] X. Fang, F. Li, and N. Gao, "Probabilistic Available Transfer Capability Evaluation for Power Systems with High-Penetration Wind Power," in *13th International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, 2014, pp. 1–6.
- [132] "Form EIA-860 Annual Electric Generator Report." [Online]. Available: <https://catalog.data.gov/dataset/form-eia-860-annual-electric-generator-report-a3f6a>.
- [133] S. Lindenberg, B. Smith, and K. O'Dell, "20% Wind energy by 2030: increasing wind energy's contribution to US electricity supply," 2008. [Online]. Available: http://www.20percentwind.org/20percent_wind_energy_report_revOct08.pdf.
- [134] H. Huang and F. Li, "Sensitivity analysis of load-damping characteristic in power system frequency regulation," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 1324–1335, 2013.
- [135] Q. Shi, H. Hu, W. Xu, and J. Yong, "Low-order harmonic characteristic of photovoltaic inverters," *Int. J. Electr. Energy Syst.*, vol. 26, pp. 347–364, 2016.
- [136] H. Hu, Q. Shi, Z. He, J. He, and S. Gao, "Potential harmonic resonance impacts of PV inverter filters on distribution systems," *IEEE Trans. Sustain. Energy*, vol. 6, no. 1, pp.

- 151–161, 2015.
- [137] Q. Shi, “Power Quality Impact of Photovoltaic Systems on Residential Distribution Networks,” University of Alberta, 2014.
- [138] X. Fang, H. Cui, F. Li, L. Bai, and H. Yuan, “Risk Constrained Scheduling of Energy Storage System for Load Serving Entities Considering Load and LMP Uncertainties,” in *IFAC-Control of Transmission and Distribution Smart Grids*, 2016, pp. 1–6.
- [139] L. Bai, F. Li, Q. Hu, H. Cui, and X. Fang, “Application of Battery-Supercapacitor Energy Storage System for Smoothing Wind Power Output: An Optimal Coordinated Control Strategy,” in *IEEE PES General Meeting*, 2016, pp. 1–5.
- [140] “Energy Storage.” [Online]. Available: <http://www.cpuc.ca.gov/General.aspx?id=3462>.
- [141] M. Korpaas, A. T. Holen, and R. Hildrum, “Operation and sizing of energy storage for wind power plants in a market system,” *Int. J. Electr. Power Energy Syst.*, vol. 25, no. 8, pp. 599–606, 2003.
- [142] J. García-gonzález, R. Moraga Ruiz de la Muela, L. M. Santos, and A. M. Gonzalez, “Stochastic joint optimization of wind generation and pumped-s torage units in an electricity market,” *IEEE Trans. Power Syst.*, vol. 23, no. 2, pp. 460–468, 2008.
- [143] A. A. S. De La Nieta, J. Contreras, and J. I. Muñoz, “Optimal coordinated wind-hydro bidding strategies in day-ahead markets,” *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 798–809, 2013.

- [144] F. Garcia-Torres and C. Bordons, "Optimal Economical Schedule of Hydrogen-Based Microgrids With Hybrid Storage Using Model Predictive Control," *IEEE Trans. Ind. Electron.*, vol. 62, no. 8, pp. 5195–5207, 2015.
- [145] L. Bai, Q. Hu, F. Li, T. Ding, and H. Sun, "Robust Mean-Variance Optimization Model for Grid-connected Microgrids," in *IEEE PES General Meeting*, 2015, pp. 1–5.
- [146] J. Xiao, L. Bai, Z. Lu, and K. Wang, "Method, implementation and application of energy storage system designing," *Int. J. Electr. Energy Syst.*, vol. 24, pp. 378–394, 2014.
- [147] J. Xiao, L. Bai, F. Li, H. Liang, and C. Wang, "Sizing of energy storage and diesel generators in an isolated microgrid Using Discrete Fourier Transform (DFT)," *IEEE Trans. Sustain. Energy*, vol. 5, no. 3, pp. 907–916, 2014.
- [148] B. C. Ummels, E. Pelgrum, and W. L. Kling, "Integration of large-scale wind power and use of energy storage in the Netherlands' electricity supply," *IET Renew. Power Gener.*, vol. 2, no. 1, pp. 34–46, 2007.
- [149] R. A. Jabr, I. Dzafic, and B. C. Pal, "Robust optimization of storage investment on transmission networks," *IEEE Trans. Power Syst.*, vol. 30, no. 1, pp. 531–539, 2015.
- [150] W. Hu, C. Su, Z. Chen, and B. Bak-Jensen, "Optimal operation of plug-in electric vehicles in power systems with high wind power penetrations," *IEEE Trans. Sustain. Energy*, vol. 4, no. 3, pp. 577–585, 2013.
- [151] W. Su and M.-Y. Chow, "Performance evaluation of an EDA-based large-scale plug-in hybrid electric vehicle charging algorithm," *Smart Grid, IEEE Trans.*, vol. 3, no. 1, pp.

308–315, 2012.

- [152] H. Cui, F. Li, X. Fang, and R. Long, “Distribution Network Reconfiguration with Aggregated Electric Vehicle Charging Strategy,” in *IEEE PES General Meeting*, 2015, no. 1, pp. 1–5.
- [153] M. Korpas and a. T. Holen, “Operation Planning of Hydrogen Storage Connected to Wind Power Operating in a Power Market,” *IEEE Trans. Energy Convers.*, vol. 21, no. 3, pp. 742–749, 2006.
- [154] E. Moiseeva, M. R. Hesamzadeh, and D. R. Biggar, “Exercise of Market Power on Ramp Rate in Wind-Integrated Power Systems,” *IEEE Trans. Power Syst.*, vol. 30, no. 3, pp. 1614–1623, 2015.
- [155] R. Bo and F. Li, “Probabilistic LMP forecasting considering load uncertainty,” *IEEE Trans. Power Syst.*, vol. 24, no. 3, pp. 1279–1289, 2009.
- [156] D. Villanueva, J. L. Pazos, and A. Feijóo, “Probabilistic load flow including wind power generation,” *IEEE Trans. Power Syst.*, vol. 26, no. 3, pp. 1659–1667, 2011.

APPENDIX

PUBLICATIONS DURING PH.D. STUDY

Related Journal Papers

- [J1] **Xin Fang**, Fangxing Li, Yanli Wei, Riyasat Azim and Yan Xu, “Reactive Power Planning with High Penetration of Wind Energy using Benders Decomposition,” *IET Gener. Transm. Distrib.*, vol. 9, no. 14, pp. 1835–1844, Nov. 2015.
- [J2] **Xin Fang**, Qinran Hu, Fangxing Li, Beibei Wang, Yang Li, “Coupon-Based Demand Response Considering Wind Power Uncertainty: A Strategic Bidding Model for Load Serving Entities,” *IEEE Trans. Power Syst.*, vol. 31, no. 2, pp. 1025–1037, March 2016.
- [J3] **Xin Fang**, Fangxing Li, Yanli Wei, Hantao Cui, “Strategic scheduling of energy storage for load serving entities in locational marginal pricing market,” *IET Gener., Transm. Distrib.*, vol. 10, issue 5, pp. 1258–1267, April 2016.
- [J4] **Xin Fang**, Yanli Wei, Fangxing Li, “Evaluation of LMP Intervals Considering Wind Power Uncertainty,” *IEEE Trans. Power Syst.*, vol. 31, no. 3, pp. 2495-2496, May 2016.
- [J5] **Xin Fang**, Fangxing Li, Qinran Hu, Yanli Wei, “Strategic CBDR Bidding Considering FTR and Wind Power,” *IET Gener. Transm. Distrib.*, vol. 10, issue 10, pp. 2464-2474, July 2016.
- [J6] **Xin Fang**, Fangxing Li, “LMP Risk Components Considering Wind Power Uncertainty,” *IEEE Trans. Power Systems*, under revision.
- [J7] Beibei Wang, **Xin Fang**, Xiayang Zhao, Houhe Chen, “Bi-level Optimization for Available Transfer Capability Evaluation in Deregulated Electricity Market,” *Energies*, 2015, 8(12). 13344-13360.
- [J8] Hantao Cui, Fangxing Li, Qianran Hu, Linqun Bai, **Xin Fang**, “Day-ahead Coordinated Operation of Utility-Scale Electricity and Natural Gas Networks Considering Demand

Response Based Virtual Power Plants” *Applied Energy.*, vol. 176, no. 15, pp. 183-195, 2016.

- [J9] Hantao Cui, Fangxing Li, **Xin Fang**, “Arbitrage Potential Evaluation for Grid-Scale Energy Storage considering High-Penetration Wind Power,” *IET Gener. Transm. Distrib.*, Under Revision.
- [J10] Qinran Hu, Fangxing Li, **Xin Fang**, Linqun Bai, “An Optimal Framework of Incentive based Residential Demand Aggregation,” *IEEE Trans. Smart Grid*, Under Revision.
- [J11] Houhe Chen, **Xin Fang**, Fangxing Li, “Available Transfer Capability Evaluation in Deregulated Electricity Market Considering Correlated Wind Power,” *IEEE Trans. Sustain. Energy*, Under Revision.

Conference Papers

- [C1] **Xin Fang**, Fangxing Li, Yan Xu, “Reactive Power Planning Considering High Penetration of Wind Energy,” *IEEE PES T&D Conf. and Expo. 2014*, Chicago, IL, April 14-17, 2014.
- [C2] **Xin Fang**, Fangxing Li, Ningchao Gao, “Probabilistic Available Transfer Capability Evaluation with High Penetration of Wind Power,” *13th International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, Durham, UK, July 07-10, 2014.
- [C3] **Xin Fang**, Fangxing Li, Ningchao Gao, and Qiang Guo, “Available Transfer Capability of Photovoltaic Generation Incorporated System,” *IEEE PES General Meeting 2014*, National Harbor, MD, July 27-31, 2014.
- [C4] **Xin Fang**, Fangxing Li, Qinran Hu, Ningchao Gao, “The Impact of FTR on LSE’s Strategic Bidding considering Coupon based Demand Response,” *IEEE PES General Meeting 2015*, Denver, CO, July 26-30, 2015.

- [C5] Qinran Hu, **Xin Fang**, Fangxing Li, “An Approach to Assess the Responsive Residential Demand to Financial Incentives,” *IEEE PES General Meeting 2015*, Denver, CO, July 26-30, 2015.
- [C6] Hantao Cui, Fangxing Li, **Xin Fang**, “Distribution Network Reconfiguration with Aggregated Electric Vehicle Charging Strategy,” *IEEE PES General Meeting 2015*, Denver, CO, July 26-30, 2015.
- [C7] **Xin Fang**, Fangxing Li, Qinran Hu, Ningchao Gao, “System Load Margin Evaluation using Mixed-Integer Conic Optimization,” *North America Power System (NAPS) 2015*, Charlotte, NC, Oct. 3-6, 2015.
- [C8] Haoyu Yuan, Xue Li, Fangxing Li, **Xin Fang**, Hantao Cui, Qinran Hu, “Mitigate Overestimation of Voltage Stability Margin by Coupled Single-Port Circuit Models,” *IEEE PES General Meeting 2016*, Boston, MA, July 21-26, 2016.
- [C9] Linqun Bai, Fangxing Li, Qinran Hu, Hantao Cui, **Xin Fang**, “Application of Battery-Supercapacitor Energy Storage System for Smoothing Wind Power Output: An Optimal Coordinated Control Strategy,” *IEEE PES General Meeting 2016*, Boston, MA, July 21-26, 2016.
- [C10] **Xin Fang**, Hantao Cui, Fangxing Li, Linqun Bai, Haoyu Yuan “Risk Constrained Scheduling of Energy Storage System for Load Serving Entities Considering Load and LMP Uncertainties,” *IFAC- Control of Transmission and Distribution Smart Grids 2016*, submitted.

VITA

Xin Fang joined Professor Fangxing Li's group in The University of Tennessee at Knoxville in August 2012 to pursue the Ph.D. degree in Electrical Engineering. He received his B.S. degree from Huazhong University of Science & Technology, Wuhan, China, in 2009, and M.S. degree from China Electric Power Research Institute, Beijing, China, in 2012. His research interests include electricity market operation, reactive power planning, demand response and renewable energy integration.