Game-theoretic Analysis of Australia's National Electricity Market (NEM) under Renewables and Storage Integration

Amin Masoumzadeh

Submitted in partial fulfilment of the requirements of the degree of

Doctor of Philosophy

Department of Electrical and Electronic Engineering
THE UNIVERSITY OF MELBOURNE

June 2018

Abstract

ELECTRICITY markets face multiple challenges such as intermittent electricity generation, high levels of average prices, and price volatility. Moreover, future electricity generation is required to be environmentally friendly, reliable and affordable. This thesis presents game-theoretic frameworks for addressing the aforementioned challenges in electricity markets. In our simulations, we apply and evaluate our developed competitive electricity market models to Australia's National Electricity Market (NEM).

We extend an existing Cournot-based wholesale electricity market model by considering strategic storage players in addition to generation and transmission players. This allows us to model the strategic behavior of storage players in future electricity markets, which can significantly help to reduce the price volatility.

The problem of high levels of price volatility in electricity markets might be related to the closure of base-load coal power plants or the fast growing expansion of wind power generation. Using our Cournot-based model, we design a storage allocation framework to find the optimal regional storage capacities to limit the price volatility in the market to a certain level. The results show how the impacts of strategic and regulated storage firms differ in reducing the price volatility in the market.

We next study the market power problem, which is one of the main contributors to high levels of power prices and price volatility in electricity markets. We develop an optimization model for allocating a fixed budget on regulated wind and storage capacities to increase the competition and reduce the weighted sum of average price and price volatility in an electricity market. The results indicate that storage is more effective in price volatility reduction than wind, whereas wind is more efficient in average price reduction.

We then study the tax and subsidy policies which can lead to emission reduction and reliability enhancement in electricity markets. We extend our developed Cournot-based electricity market model as a long-term generation expansion model with an upper bound on CO_2 emission in the market. In addition to the future generation capacity portfolio, this model proposes the carbon tax levels required to achieve the carbon abatement target in the market.

The policies imposed in electricity markets for emission reduction targets may lead to large investments on intermittent renewable energies. Designing a low carbon and reliable electricity market, we develop a long-term market expansion model with emission reduction and dispatchable capacity constraints. The model is used to calculate the tax and subsidy on CO_2 emission and fast response dispatchable capacity, which can lead to transition towards a green and reliable electricity market in Australia.

Declaration

This is to certify that

1. the thesis comprises only my original work towards the PhD,
2. due acknowledgement has been made in the text to all other material used,
3. the thesis is less than 100,000 words in length, exclusive of tables, maps, bibliographies and appendices.

Amin Masoumzadeh, June 2018

Preface

The outcomes of this thesis are published or under review for publication in the following journals and conferences. This thesis was mainly done by the student. However, the student benefited from his supervisors through group meeting sessions in which they provided technical comments and guidance. Financial support provided by the University of Melbourne including Melbourne International Research Scholarship (MIRS) and Melbourne International Fee Remission Scholarship (MIFRS) are gratefully acknowledged. We also acknowledge this work was supported in part by the ARC Discovery Project DP140100819.

- Chapter 4
  - Masoumzadeh, A., Nekouei, E., & Alpcan, T. (2017, September). Impact of a Coal Power Plant Closure on a Multi-region Wholesale Electricity Market. in 2017 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), Sept 2017, pp. 16.

    The contribution of each author is as follows: First author: Designing the multi-region market model, performing simulations, and writing the paper. Second and Third Authors: Supervision, proofreading, and providing technical comments on the market model.
- Chapter 5
  - Masoumzadeh, A., Nekouei, E., Alpcan, T., & Chattopadhyay, D. (2017). Impact of Optimal Storage Allocation on Price Volatility in Energy-only Electricity Markets. IEEE Transactions on Power Systems, vol. PP, no. 99, pp. 1-1,

2017.

The contribution of each author is as follows: First author: Designing the storage allocation framework, performing simulations, and writing the paper. Second and Third Authors: Supervision, proofreading, and providing technical comments on the market model, providing proof for existence of Nash Equilibrium in our model. Fourth Author: Technical comments on the paper, improving the motivation for reducing the extreme levels of price volatility.

- Chapter 6
  - Masoumzadeh, A., Nekouei, E., & Alpcan, T. Regulated Wind-Storage Allocation to Reduce the Electricity Market Price and Volatility, submitted to IEEE Transactions on Power Systems.

    The contribution of each author is as follows: First author: Designing the wind-storage allocation framework, performing simulations, and writing the paper. Second and Third Authors: Supervision, proofreading, providing technical comments on the market model, and especially on the transmission player.
- Chapter 7
  - Masoumzadeh, A., Nekouei, E., & Alpcan, T. (2016, November). Long-term Stochastic Planning in Electricity Markets under Carbon Cap Constraint: A Bayesian Game Approach. In Innovative Smart Grid Technologies-Asia (ISGT-Asia), 2016 IEEE (pp. 466-471). IEEE.

    The contribution of each author is as follows: First author: Designing the generation expansion model, performing simulations, and writing the paper. Second and Third Authors: Supervision, proofreading, providing technical comments on the market model, and reorganizing the paper structure.
- Chapter 8
  - Masoumzadeh, A., Alpcan, T., & Nekouei, E. Designing Incentive Policies Towards a Green and Reliable Electricity Market, submitted to IEEE Transactions on Power Systems.

The contribution of each author is as follows: First author: Designing the market expansion model, performing simulations, and writing the paper. Second and Third Authors: Supervision, proofreading, providing technical comments on the market model.

Acknowledgements

I would like to express my sincere gratitude to my supervisors A/Prof. Tansu Alpcan, Dr. Ehsan Nekouei, and Prof. Robin Evans for their continuous support, patience, and invaluable constructive criticism. They made my Ph.D. a rewarding experience via their friendly and tactful supervision. The guidance from my advisors helped me in all the time of research and writing the thesis. Besides, I would like to thank my thesis committee, A/Prof. Marcus Brazil, for his insightful comments and questions.

I appreciate the financial support provided by the University of Melbourne. I also would like to thank my family and friends from my heart for their part and support during my study journey.

Contents

Nomenclature 1

1 Introduction **5**
1.1 Background 5
1.2 Research Questions 10
1.3 Literature Review and Research Gaps 12
1.4 Thesis Contributions 20
1.5 Thesis Outline 22
1.6 Publications 25

I Electricity Market Models and NEM as the Case Study **27**

2 Game-theoretic Cournot-based Electricity Market Models with Storage **31**
2.1 Introduction 31
2.2 Mathematical Model Description 32
2.3 Game-theoretic Model of a Wholesale Electricity Market 34
2.3.1 Game Definition and Nash Equilibrium: 34
2.3.2 The Game with Strategic Storage Firms 36
2.4 Multi-nodal, Multi-period Wholesale Electricity Market 39
2.4.1 The Game as a Centralized Optimization Problem 39
2.4.2 The Game as a Mixed Complementarity Problem 41
2.5 Conclusion 42

3 NEM as the Case Study **43**
3.1 Overview of National Electricity Market (NEM) 43
3.2 Calibrating the Inverse Demand Functions 45
3.3 Model Calibration with Real Data 47

II Analysis of Price Volatility in Electricity Markets **49**

4 Impact of a Coal Power Plant Closure on a Multi-region Wholesale Electricity Market **53**
4.1 Introduction 53
4.2 System Model 54

4.2.1 Wholesale Price Function 55
4.2.2 Market Participants 55
4.2.3 Solution Approach 58
4.3 Case Study and Simulation Results 59
4.3.1 Model Calibration 59
4.3.2 Model Simulation for 365 Days 60
4.4 Conclusion 65

5 Impact of Optimal Storage Allocation on Price Volatility in Electricity Markets 67
5.1 Introduction 67
5.2 System Model 69
5.2.1 Upper-level Problem 69
5.2.2 Lower-level Problem 71
5.3 Solution Approach 75
5.3.1 Game-theoretic Analysis of the Lower-level Problem 76
5.3.2 The Equivalent Single-level Problem 79
5.4 Case Study and Simulation Results 80
5.4.1 Simulations in NEM 80
5.4.2 Simulations for a 30-bus System 88
5.5 Conclusion 89

6 Regulated Wind-Storage to Reduce the Electricity Market Price and Volatility 93
6.1 Introduction 93
6.2 The Problem and Market Model 95
6.2.1 Upper-level Problem 95
6.2.2 Lower-level Problem 97
6.3 Solution Approach 103
6.3.1 Solution Method for the lower level problem 103
6.3.2 Solution Method for the equivalent single level problem 103
6.4 Case Study and Simulation Results 104
6.4.1 Impact of Generation Capacity, Gas Price and Transmission Line on Average Price and Price Volatility in NEM 105
6.4.2 Managing the Average Price and Price Volatility by Only Regulated Wind or Only Regulated Storage 106
6.4.3 Managing the Average Price and Price Volatility by Mixture of Regulated Wind and Storage in VIC 109
6.5 Conclusion 110

III Designing Incentive Policies in Electricity Markets 113

7 Long-Term Stochastic Planning in Electricity Markets with a Carbon Cap Constraint 117
7.1 Introduction 117
7.2 Game-Theoretic Formulation of Long-term Wholesale Electricity Market . 119
7.2.1 Game Definition and Bayes-Nash Equilibrium 119

7.2.2 Carbon Price Calculation as a Dual Variable 122
7.2.3 Solving the Game as a Centralized Optimization Problem 122
7.3 Numerical Analysis 123
7.3.1 Impact of Carbon Cap on Capacity Planning 124
7.3.2 Impact of Wind Stochasticity on Carbon Price 125
7.3.3 Impact of Wind Player's Strategic Behavior on Capacity Planning . 126
7.3.4 Impact of Remaining Value on Capacity Planning 128
7.4 Conclusion 129

8 Designing Tax&Subsidy Incentives Towards a Green and Reliable Electricity Market 131
8.1 Introduction 131
8.2 Strategically Competitive Electricity Market Expansion Model 133
8.2.1 Inverse Demand Functions 133
8.2.2 Total Capacity and Investment Functions 134
8.2.3 The Emission and Capacity Incentive Policies 135
8.2.4 The Market Expansion Game 136
8.3 Solution Methodology 141
8.3.1 Game-theoretic Analysis of the Market Expansion Model 141
8.3.2 The Mixed Complementarity Problem 144
8.3.3 Interpreting the Dual Variables as Tax and Subsidy 145
8.3.4 The Market Expansion Model in Practice 145
8.4 Case Study and Simulation Results 147
8.4.1 Impact of Emission Reduction Policy on Market Expansion 147
8.4.2 Impact of Emission Reduction Policy on Electricity Prices and Demands 149
8.4.3 Carbon Tax&Subsidy Design 150
8.4.4 Fast Response Capacity Tax&Subsidy Design 152
8.4.5 Impact of Market Power on Market Expansion 153
8.5 Conclusion 154

9 Conclusions 157
9.1 Summary of Chapters and Conclusions 157
9.2 Future Research 161

A Charging/Discharging 163

B Regulated Transmission Firms 165

C Technology Characteristics 167

List of Figures

1.1 Three main criteria in designing the future electricity markets. 5

2.1 Storage charging and discharging effects on supply/demand equilibrium point at a given moment in time (points 1 and 2 represent equilibrium point before and after storage installation). 38

3.1 Interconnected states in Australia's National Electricity Market. 43
3.2 Dispatchable and intermittent electricity generation capacities in the NEM, 2017. 44
3.3 The clearing engine mechanism in the NEM (Source: AEMO). 45
3.4 Calibrated linear, exponential and iso-elastic inverse demand functions at price 50 $/MWh, demand 1500 MW, and elasticity -0.3. 47
3.5 Comparing the simulation results (solid lines) of hourly price and demand with the historical data (dashed lines) (Source: AEMO) for the average day of 2017 in five states of the NEM. 48

4.1 Sorted historical data of hourly (a) electricity demand and (b) wind power availability in five regions of NEM during the year 2015. 61
4.2 Probability distribution of hourly prices in NEM and VIC, considering the closure of coal power plant Hazelwood in VIC. 62
4.3 Probability distribution of daily peak prices in NEM and VIC, considering the closure of coal power plant Hazelwood in VIC. 63

5.1 SA's Hourly wind power availability distribution in 2015 (the central marks show the average levels and the bottom and top edges of the boxes indicate the 25th and 75th percentiles). 82
5.2 Standard deviation and mean of hourly wholesale electricity prices in SA with no storage. 83
5.3 Optimal strategic and regulated storage capacity for achieving different price volatility levels in SA region for a high demand day with coal-plant outage. 84
5.4 Daily peak and average prices in SA versus storage capacity in a high demand day with coal-plant outage. 85
5.5 Square root of price volatility in SA versus storage capacity during a high demand day with coal-plant outage. 86

5.6 Optimal regulated storage capacity versus the percentage of price volatility reduction in the two-node market in a high demand day with coal-plant outage in SA. 88
5.7 Square root of price volatility level in the 30-bus system after ten iterations of Algorithm 1 with $\Delta Q^{st} = 15$MWh. 90

6.1 Mean (over 365 scenarios) wholesale electricity prices in VIC before and after addition of only 5000 MWh regulated battery storage capacity. 107
6.2 Mean (over 365 scenarios) wholesale electricity prices in VIC before and after addition of only 3125 MW regulated wind generation capacity. 108
6.3 The mean price, the square root of price volatility, and the life time rate of return for only regulated wind and only regulated battery allocation versus the equivalent annual budget in VIC. 109
6.4 Normalized mean wholesale price and square root of price volatility for different mixtures of regulated wind and regulated battery with the equivalent annual budget of 300 m$ in VIC. 110
6.5 The budget allocation share between the regulated wind and the regulated battery as a function of the weighting factor k with the equivalent annual budget of 300 m$ in VIC. 111

7.1 Normalized wind capacity availability (ω_t) during off-peak, shoulder, and peak load zones, distributed on $[(1\text{-}\sigma)E(\omega), (1\text{+}\sigma)E(\omega)]$ with the given expected value $E(\omega)$ 125
7.2 Capacity investment Q^{total} and its change ΔQ^{total} due to carbon cap constraint with coefficient $\phi \in \{20, 40\%\}$. 126
7.3 Carbon pricing for different CO_2 emission reduction scenarios ($\phi \in \{20\ \%, 60\ \%\}$). 127
7.4 New capacity installation Q^{new} considering wind strategy (perfectly competitive and strategic). 127
7.5 New capacity installation considering remaining value. 128

8.1 Normalized investment cost of generation and storage technologies during 2017-2052 (Normalization is compared to the costs in 2017). 148
8.2 Net increase/decrease of capacity for (a) generation and (b) storage and transmission technologies by 2052 in NEM for different target levels of emission intensity reduction. 149
8.3 The average yearly (a) wholesale prices and (b) net and wholesale demands in NEM, without or with emission reduction policy (net demand =wholesale demand + roof-top PV). 151
8.4 The trajectory of (a) carbon price, (b) carbon tax (positive) and subsidy (negative) of different generation types during 2017-2052. 152
8.5 The trajectory of fast response capacity tax (positive) and subsidy (negative) for (a) No Emission Reduction policy, (b) 80% Emission Intensity Reduction policy. 153

8.6 Technology capacity mix in NEM with and without considering market power for (a) No Emission Reduction policy, (b) 80% Emission Intensity Reduction policy. 154

List of Tables

4.1 Wholesale electricity prices \$/MWh in five-node NEM market, considering the closure of coal power plant Hazelwood in VIC. 61
4.2 The annual electricity generation profit (billion\$ per year) in five-node NEM market, considering the closure of coal power plant Hazelwood in VIC. 63
4.3 Standard deviation of wholesale electricity prices \$/MWh in five-node NEM market, considering the closure of coal power plant Hazelwood in VIC. 64
4.4 Greenhouse gas emission of CO_2 (million tonne per year) in coal and gas-fueled power plants in NEM, considering the closure of coal power plant Hazelwood in VIC. 64

5.1 Location, capacity and generation cost of synchronous generators in the 30-bus electricity system. 89

6.1 Wholesale electricity prices (\$/MWh) in five-node NEM market in primary and secondary cases. 106

7.1 The parameters for the inverse demand function. 124
7.2 Costs and technology specifications of generation firms. 124
7.3 Total CO_2 emission every five years in the system with no carbon cap constraint. 125

C.1 Financial and Technical Information on Intermittent Generators in NEM. . 167
C.2 Financial and Technical Information on Synchronous Generators in NEM. 168
C.3 Financial and Technical Information on Storage Technologies in NEM. . . 168
C.4 Financial and Technical Information on Interconnectors in NEM. 168

Nomenclature

Indices

m	Intermittent generation firm.
n	Synchronous generation firm.
k	Generation firm.
b	Storage firm.
i, j	Node.
y	Investment period (yr).
t	load time (hr).
w	Scenario.

Parameters

$\alpha_{iyt}, \alpha_{itw}, \alpha_{it}$	Intercept of the inverse demand function.
$\beta_{iyt}, \beta_{itw}, \beta_{it}$	Slope of the inverse demand function.
$EI_{Y_0}^{CO_2}$	CO_2 Emission intensity at base year Y_0.
$E_y^{CO_2}$	CO_2 Emission at year y.
ϕ	Emission reduction coefficient.
EF_{ni}	Emission factor of the synchronous generator.
α_y^{ER}	Emission intensity reduction target.
$\alpha_{ni}^{sg,FR}$	Binary coefficient to distinguish fast response generators.
$\alpha_{bi}^{st,FR}$	Binary coefficient to distinguish fast response storage firms.
α^{FR}	Fast response proportion coefficient.
r	Discount factor.

$Q^{\text{old}}_{y''}$	Old capacity of any generation, storage and transmission technology installed at y'', which is before the base year.
PL	Plant life of any generation, storage and transmission technology.
c^{ig}_{mi},d^{ig}_{mi}	Quadratic cost function coefficients of the intermittent generator.
γ^{ig}_{mi}	Binary parameter to distinguish if the intermittent generator is strategic/regulated.
Inv^{ig}_{miy}	Unitary investment cost of the intermittent generator.
A^{ig}_{mit}	Energy availability coefficient of the intermittent generator.
ω_{kiystw}, ω_{mitw}	Energy availability coefficient of the intermittent generator.
$\bar{C}^{\text{ig}}_{mi}$	Maximum potential capacity of the intermittent generator.
c^{sg}_{ni}	Marginal operation and fuel cost of the synchronous generator.
γ^{sg}_{ni}	Binary parameter to distinguish if the synchronous generator is strategic/regulated.
Inv^{sg}_{niy}	Unitary investment cost of the synchronous generator.
A^{sg}_{ni}	Availability coefficient of the synchronous generator.
R^{up}_{ni},R^{dn}_{ni}	Ramping up and down coefficient of the synchronous generator.
RA^{sg}_{niy}	Energy availability limit of the synchronous generator at period y.
$Inv^{\text{st}^{\text{f}}}_{biy}$	Unitary investment cost of the storage on flow capacity.
$Inv^{\text{st}^{\text{v}}}_{biy}$	Unitary investment cost of the storage on volume capacity.
η^{ch}_{bi},η^{dis}_{bi}	Charge and discharge efficiencies of the storage.
A^{st}_{bi}	Availability coefficient of the storage.
η^{tr}_{ij}	Efficiency of the transmission line.
Inv^{tr}_{ijy}	Unitary investment cost of the transmission line.
A^{tr}_{ij}	Availability coefficient of the transmission line.
Pr_w	Probability of scenario w.
$\Delta\text{l}_{y,s,t}$	length of time segment (y, s, t).
ΔY_y	length of time segment y.
ΔS_s	length of time segment s.
ΔT_t	length of time segment t.
Inv_k, m_k, c_k	Investment, maintenance and operation cost of generator k.

σ	Percentage of wind availability domain change.
$Q^{\text{ig}}, Q^{\text{sg}}, Q^{\text{st}}, Q^{\text{tr}}$	Intermittent generation, synchronous generation, storage and transmission capacities.

Variables

D_{iyt}, D_{itw}, D_{it}	Electricity demand.
$q^{\text{ig}}_{miyt}, q^{\text{ig}}_{mitw}, q^{\text{ig}}_{mit}$	Generation of the intermittent generator.
$q^{\text{sg}}_{niyt}, q^{\text{sg}}_{nitw}, q^{\text{sg}}_{nit}$	Generation of the synchronous generator.
$q^{\text{st}}_{biyt}, q^{\text{st}}_{bitw}, q^{\text{st}}_{bit}$	Electricity flow of the storage.
$q^{\text{tr}}_{ijyt}, q^{\text{tr}}_{ijtw}, q^{\text{tr}}_{ijt}$	Electricity flow from node j to node i.
$Q^{\text{ig,new}}_{miy}$	New capacity of the intermittent generator.
$Q^{\text{sg,new}}_{niy}$	New capacity of the synchronous generator.
$q^{\text{ch}}_{biyt}, q^{\text{ch}}_{bitw}, q^{\text{ch}}_{bit}$	Charge of the storage.
$q^{\text{dis}}_{biyt}, q^{\text{dis}}_{bitw}, q^{\text{dis}}_{bit}$	Discharge of the storage.
$Q^{\text{st}^{\text{f}},\text{new}}_{biy}$	New flow capacity of the storage.
$Q^{\text{st}^{\text{v}},\text{new}}_{biy}$	New volume capacity of the storage.
$Q^{\text{tr,new}}_{ijy}$	New capacity of the transmission line.

Functions

$P_{iyt}(.), P_{itw}(.), P_{it}(.)$	Wholesale price.
$Q^{\text{ig}}_{miy}(.)$	Total capacity of the intermittent generator.
$Q^{\text{sg}}_{niy}(.)$	Total capacity of the synchronous generator.
$Q^{\text{st}^{\text{f}}}_{biy}(.)$	Total flow capacity of the storage.
$Q^{\text{st}^{\text{v}}}_{biy}(.)$	Total volume capacity of the storage.
$Q^{\text{tr}}_{ijy}(.)$	Total capacity of the transmission line.

Chapter 1
Introduction

1.1 Background

ELECTRICITY generation industry in many countries around the world has experienced a significant transformation from being a centrally coordinated monopoly to a deregulated competitive market, during the last three decades (since 1990) [1]. The existing electricity markets have to overcome some challenges including: (*i*) the over- and under-capacity in generation, transmission and distribution, which are imposing costs on market participants and also the market power that leads to electricity prices significantly above the electricity generation costs; (*ii*) the intermittent renewable integration into the networks, and the system reliability; and (*iii*) high levels of CO_2 emission intensity in electricity generation sector and the challenges for de-carbonization of electricity markets. Therefore, electricity is aimed to be green, reliable and affordable in future electricity markets, as shown in Fig. 1.1.

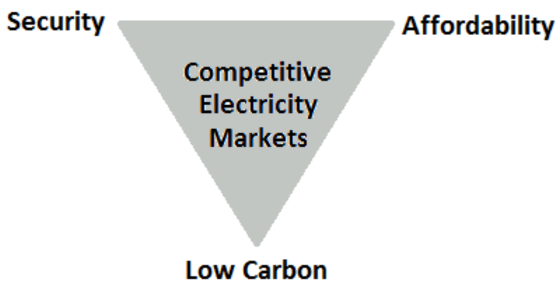

Figure 1.1: Three main criteria in designing the future electricity markets.

However, these three factors are highly interrelated and we need to study them simultaneously. For instance, storage is expected to be installed in electricity networks to increase the system reliability and decrease the average price and price volatility; closure of coal power plants lowers the emission in the market but may lead to price increase and volatility problem; although integration of wind and solar in power grids leads to more clean electricity generation, it brings high levels of price volatility in the network; although wind and storage both can remedy the high levels of average price and price volatility in the market, their impacts on price reduction and volatility reduction are not the same; and electricity generation technologies need to be taxed and subsidized at the same time. Wind turbines need to be subsidized as they generate clean electricity and need to be penalized as they bring intermittency in electricity networks.

Storage Integration in Power Grids:

Given the continuing decrease in battery costs, a large amount of battery storage capacity is expected to be installed in transmission and/or distribution networks in the near future. Moreover, global roadmap vision indicates significant capacity increase for pump-storage hydro power, from 140 GW in 2012 to 400 to 700 GW in 2050 [2]. Storage can be used for multiple purposes including reduction in expensive peaking capacity, managing intermittency of distributed wind/solar generation, and managing excess generation from base-load coal/nuclear during off-peak times. By providing virtual generation capacity, storage may alleviate existing problems by reducing the impacts of intermittent power generation, market power, and volatility.

Coal Plant Closure and Price Volatility Problem:

The exercise of very high prices and price volatility can be the result of closing base-load power plants down in electricity markets. In many countries, base-load coal power plants are being closed due to either reaching their end of life, or being scheduled as part of their national greenhouse reduction schemes [3]. In wholesale electricity markets with high percentage of intermittent renewable generation, closure of base-load power plants may lead to high electricity prices and increased volatility, which exposes the market participants to a high level of financial risks. Over the past three years, four big coal-fueled power plants closed down in Australia's National Electricity Market (NEM). The closure of Victoria's second biggest generator Hazelwood, with a 1600 MW capacity, in 2017 was a highly debated topic in the press. The impact of a coal plant closure on market prices can be measured in advance, which might be significant especially in highly renewable penetrated networks.

Renewable Integration and Price Volatility Problem:

A high level of intermittent wind generation may also result in frequent high prices and high levels of price volatility in electricity markets [4–6]. High levels of price volatility in a market refers to a situation in which the market prices vary in a wide range. For example, one hundred hours with highest levels of electricity prices resulted in 21% of the annual monetary market share in 2015 in South Australia, which is a highly price volatile region in the NEM market [7]. Price volatility makes the task of price prediction highly uncertain, which consequently imposes large financial risks on the market participants. In the long term, extreme levels of price volatility can lead to undesirable consequences such as bankruptcy of retailers [8] and market suspension. In a highly volatile electricity market, the participants, such as generators, utility companies and large industrial consumers, are exposed to a high level of financial risk as well as costly risk management strategies [9]. In some electricity markets, such as the NEM, the market is suspended if the sum of spot prices over a certain period of time is more than cumulative price threshold (CPT). A highly volatile market is subject to frequent CPT breaches due to the low conventional capacity and high level of wind variability. Storage, with price arbitrage capability, can resolve the problem of high electricity prices and consequently it can prevent high levels of price volatility. We note that recently a large scale storage installation has been announced in South Australia for resolving the price volatility as well as the reliability problems.

Average Price and Price Volatility Problem:

In addition to extreme levels of price volatility, high levels of average prices are also undesirable in electricity markets. Closure of coal power plants and the fluctuation of gas price may result in high levels of average price and price volatility in electricity markets [10]. For example, Australia's National Electricity Market (NEM) has experienced very high prices after the closure of Hazelwood coal power plant and the surge of gas price [11]. As we discussed, price volatility imposes large financial risks on the market participants by increasing the future price prediction uncertainty. On the other hand, high levels of mean wholesale electricity prices lead to higher retail prices, i.e., impose high cost on consumers.

One of the main reasons behind high electricity prices in highly concentrated electricity markets, such as NEM, is high levels of market power [7, 12]. Electricity markets are less likely to be successful and stable in the presence of market power. When market power is diagnosed to be persistent, more government intervention may pave the way towards an efficient market as the private sector is likely to act slowly due to regulatory, institutional, or other barriers [13]. In such cases, the government may choose to intervene and install regulated wind and storage capacities, which have short construction periods, to increase the competition in the market and reduce the market power as well as the electricity prices [5].

Penalizing Carbon Emission and Supporting Dispatchable Capacity:

On the other hand, instead of controlling the firms, governments can influence the market by setting effective tax and subsidy schemes. Market expansion models can be used to design tax and subsidy schemes required to achieve long-term goals, like emission reduction strategies and maintaining reliability in the network.

In market expansion models for competitive power markets, electricity price is not set by regulators but by the equilibrium between electricity supply and demand. In order to make investment and operation decisions, generation companies have a strong interest in modeling anticipated prices using available engineering and economic information. They need appropriate decision making models considering not only technical operation constraints but also the interaction among market participants. A variety of physical and economic factors are included in market modeling, many of which are stochastic by nature. Moreover, policy makers can intervene and incentivize the market players to meet their desired goals, such as caps on carbon emission.

Future electricity markets require to be green, reliable, and efficient. Greenhouse gas reduction from power generation has been firmly on the political agenda recently, following the international commitments under the Kyoto (1997) and Paris (2015) Agreements [14]. The policies imposing an emission target level in the electricity sector affects many existing fossil-fueled power plants as well as the future generation mix. Moreover, the emission reduction policies may lead to massive investment in renewable generation. High penetration of Variable Renewable Energy (VRE) in an electricity network can pose challenges to system reliability. Additional fast response dispatchable capacity must be introduced to the system to complement an increasing proportion of VRE generators such as wind and solar photovoltaic [15]. This may lead to new obligations for VRE generators connected to NEM to ensure that the system reliability is maintained. Although the decline in technology cost enables renewables to compete with fossil-fueled plants in electricity generation, the incentive policies can be used to accelerate the ongoing transition toward a green network.

Australia's National Electricity Market (NEM):

In the NEM, electricity is an ideal commodity which is exchanged between producers and consumers through a pool. The market operator must ensure the agreed standards of security and reliability. Security of electricity supply is a measure of the power system capacity to continue operating despite the disconnection of a major generator or interconnector. In fact, unserved demand per year for each region must not exceed 0.002 percent of the total energy consumed. This level of reliability across the NEM requires a certain level of reserve. However, when security and reliability is threatened, the market operator is equipped with a variety of tools including demand side management, load shedding and reserve trading to maintain the supply and demand balance.

Operating the NEM consists of estimating the electricity demand levels, receiving the bidding offers, scheduling and dispatching the generators, calculating the spot price and financially settling the market. Electricity demand in a region is forecasted based on different factors, like population, temperature and sectoral energy consumption in that region. Electricity supply bids (offers) are submitted in three forms of daily bids, re-bids and default bids [16]. Using the rising-price stack, generators are scheduled and dispatched in the market.

1.2 Research Questions

In this thesis, we develop wholesale electricity market models to answer the following research questions.

Research Question 1: How can we model strategic storage firms in a competitive electricity market?

Large amounts of storage capacity are expected to be installed in power grids, which impact the electricity prices at peak and off-peak times, and the electricity dispatch from intermittent and classical generators in the market. In addition to generation and transmission players, storage players impact the total amounts of electricity generation and demand in an electricity market. We develop an electricity market model considering the interaction between strategic storage firms with generation, and transmission players. We address this research question and the related issues in Chapter 2.

Research Question 2: What is the impact of a coal plant closure on electricity prices in a multi-region wholesale electricity market?

The prices may change from very high levels to low levels or vice versa as a consequence of generation capacity closure (coal closure) or storage integration in a wholesale electricity market. The existing electricity market models are mostly developed based on linear inverse demand functions, which may not accurately indicate the relation between price and demand. Electricity market models including generation and storage players with non-linear inverse demand functions exist in the literature as single-region models. We develop multi-region wholesale electricity market models with non-linear inverse demand functions, which can precisely capture the price and demand relation, and use them to find the impact of a coal power plant closure on electricity prices in different nodes of an electricity market. We address this research question in Chapters 3 and 4.

Research Question 3: How can we find the optimal storage allocation to limit the price volatility in a competitive electricity market?

The fast growing expansion of wind power generation may lead to extremely high levels of price volatility in wholesale electricity markets. Storage capacities in electricity networks in any form of pump-storage hydro, large scale or distributed batteries can help to reduce the price volatility significantly in the market. It is important to find the optimal size and location of required storage capacities, which can limit the price volatility in an electricity market. Therefore, we develop an optimization model to solve the storage allocation problem in a multi-region wholesale electricity market model including generation, storage and transmission players. We address this research question in Chapter 5.

Research Question 4: How can we find the optimal wind and storage allocation to reduce the average price and price volatility in a competitive electricity market?

High levels of average price and price volatility in an electricity market can be the consequence of a coal power plant closure or gas price fluctuation. Installing regulated wind and storage capacities can lead to significant price and volatility reduction amounts in the market. The impacts of wind and storage on the average price and on the price volatility are different from each other. Therefore, we intend to develop an optimization model to find the optimal wind and storage capacities in order to minimize the weighted sum of average price and price volatility in the market. We address this research question in Chapter 6.

Research Question 5: How can we calculate the required carbon price in a competitive electricity market to limit the CO_2 emission?

Carbon price in an electricity market provides incentives for carbon emission abatement and renewable generation technologies. Penalizing carbon emission can significantly impact the capacity planning decisions of both fossil-fueled and renewable generators. We intend to calculate the amounts of carbon price or carbon tax that can fulfill an emission abatement target in an electricity market. We address this research question in Chapter 7.

Research Question 6: How can we design tax&subsidy incentive policies which leads to a green and reliable electricity market?

Incentive schemes and policies play an important role in reducing carbon emission from electricity generation sector. Emission abatement policies lead to more intermittent renewable generation in the market, which may endanger the market reliability. Therefore, in addition to setting incentive policies on emission reduction, we require another set of policies to encourage more fast response dispatchable capacity to ensure the balance between supply and demand (reliability) at all times in the market. We intend to calculate the incentive policies on emission and dispatchable capacities in order to transit towards a low carbon and reliable electricity market in long-term. We address this research question in Chapter 8.

1.3 Literature Review and Research Gaps

In this thesis, we develop Cournot-based electricity market models with generation, storage, and transmission players to address the market operation and planning issues related to designing a green, reliable and efficient electricity market. The literature review on the research questions given in Section 1.2, and the corresponding research gaps are discussed below.

Literature on Research Question 1: Cournot-based Electricity Market Models and Storage Integration

Classical cost-minimization and surplus-maximization models for electricity generation do not incorporate strategic behaviors [1, 17]. Game theoretic models including Cournot-Nash models are capable of computing market equilibrium considering strategic behaviors, which originates from the players' market power [18]. For example, a comprehensive analysis of Australian electricity sector in both least-cost and Cournot schemes is discussed in [19], which states that the price bids may be significantly above the marginal cost depending on the level of competition. Classical Cournot-based models are modified in the literature to study different affecting issues in electricity markets, such as strategic interaction in electricity transmission networks [20], co-optimization of ancillary services [21], joint evaluation of maintenance and generation strategies [22], transforming energy-only markets to capacity-energy markets [23], considering volatile renewable generation [7], and introducing storage players in the market [24]. Note that Storage is modeled in a receding horizon problem in [25], in a double auction problem in [26], and in a competitive electricity market model in [27], but not in a multi-region Cournot-based electricity market model.

Therefore, to the best of our knowledge, the problem of modeling storage firms as strategic players in multi-region Cournot-based electricity market models has not been addressed before.

Literature on Research Question 2: Multi-region Cournot-based Electricity Market Models

Electricity system modeling has changed significantly after the transformation of the electricity industry from being a regulated monopoly to a deregulated competitive market in many countries around the world [1]. Game-theoretical models have been extensively used in imperfect competitive energy system analysis to calculate the price and generation quantities in a market [28]. The problem of finding the equilibrium price and generation in an electricity market, which consists of generation firms, transmission lines and consumers, has been studied by solving the game-theoretical profit maximization Cournot-based (quantity bidding) problems, e.g. in [7, 19–21, 23, 29–33], and Bertrand-based (price bidding) or supply function-based problems, e.g. in [34–36]. However, the multi-region non-cooperative electricity market models including non-linear inverse demand functions have not been investigated in the literature.

The paper [29] studies a single-region electricity market in which firms compete in quantity as in the Nash-Cournot game, and formulates the problem as a Linear Complementarity Problem (LCP). The paper [30] models the imperfect competition among electricity producers as an LCP problem, in which the players consider the spacial price discrimination to model the transmission lines in the market. The papers [20, 31] model the transmission lines in electricity markets using a bi-level model in which strategic generators bid on their quantities in the upper level and a clearing engine with transmission constraints clears the market in the lower level. Moreover, the multi-region electricity market is formulated as a centralized convex optimization problem to make long-term planning decisions [32], to include greenhouse gas reduction constraint [19], to introduce capacity market beside an energy market [23], to analyze interrelated markets for different commodities [21], and to observe the volatility of wind power [7]. The paper [33] formulates a centralized convex optimization problem to find the price of carbon emission in an electricity market. We note that these works are restricted to linear inverse demand functions, which are the first order approximation terms at their nominal points and may become imprecise approximations when the operational points change, for multi-region market modeling.

The papers [34, 35] study the multi-region electricity market using a bi-level supply function-based model in which the strategic generators bid on their supply function in the upper level and a clearing engine with transmission constraints clears the market in the lower level. The market participants strategically bid just on their prices in the upper level of the market model in [36]. Although it is possible to extend the model formulation in these works to consider non-linear inverse demand functions, they have to deal with cumbersome computations pertaining to using the bi-level models.

To the best of our knowledge, the problem of solving a multi-region non-cooperative electricity market with nonlinear inverse demand functions has not been addressed before.

Literature on Research Question 3: Storage Allocation in Wholesale Electricity Markets

The problem of optimal storage operation or storage allocation for facilitating the integration of intermittent renewable energy generators in electricity networks has been studied in [37–44], with total cost minimization objective functions, and in [45–50], with profit maximization goals. However, the price volatility management problem using optimal storage allocation has not been investigated in the literature.

The operation of a storage system is optimized, by minimizing the total operation costs in the network, to facilitate the integration of intermittent renewable resources in power systems in [37]. Minimum (operational/installation) cost storage allocation problem for renewable integrated power systems is studied in [38–40] under deterministic wind models, and in [41] under a stochastic wind model. The minimum-cost storage allocation problem is studied in a bi-level problem in [42,43], with the upper and lower levels optimizing the allocation and the operation, respectively. The paper [44] investigates the optimal sizing, siting, and operation strategies for a storage system to be installed in a distribution company controlled area. We note that these works only study the minimum cost storage allocation or operation problems, and do not investigate the interplay between the storage firms and other participants in the market.

The paper [45] studies the optimal operation of a storage unit, with a given capacity, which aims to maximize its profit in the market from energy arbitrage and provision of regulation and frequency response services. The paper [46] computes the optimal supply and demand bids of a storage unit so as to maximize the storage's profit from energy arbitrage in the day-ahead and the next 24 hour-ahead markets. The paper [47] investigates the profit maximization problem for a group of independently-operated investor-owned storage units which offer both energy and reserve in both day-ahead and hour-ahead markets. In these works, the storage is modeled as a price taker firm due to its small capacity.

The operation of a price maker storage device is optimized using a bi-level stochastic optimization model, with the lower level clearing the market and the upper level maximizing the storage profit by bidding on price and charge/discharge in [48]. The storage size in addition to its operation is optimized in the upper level problem in [49] when the lower level problem clears the market. Note that the price bids of market participants other than the storage firm are treated exogenously in these models. The paper [50] also maximizes the day-ahead profit of a load serving entity which owns large-scale storage capacity, assuming the price bids in the wholesale market as exogenous parameters.

The paper [51] maximizes a large-scale energy storage system's profit considering the storage as the only strategic player in the market. Using Cournot-based electricity market models, the generation and storage firms are considered as strategic players in [24,29]. However, they do not study storage sizing problem and the effect of intermittent renewables on the market.

Therefore, to the best of our knowledge, the problem of finding optimal storage capacity subject to a price volatility management target in electricity markets has not been addressed before.

Literature on Research Question 4: Wind-Storage Allocation in Wholesale Electricity Markets

The problem of storage allocation in the presence of intermittent renewable energy generation in electricity networks has been studied in [37–39, 41–43], using cost minimization modeling approaches, and in [24, 45–49], using profit maximization goals.

Facilitating the integration of renewable resources, the potential value of energy storage in power systems with renewable generation is evaluated by minimizing the total operation cost in the network in [37]. The optimal operation and sizing of the storage systems is studied by minimizing the cost of the system in [39]. The storage allocation in renewable integrated power systems is studied in [38] and [41] under deterministic and stochastic wind models, respectively. To accommodate the integration of renewable generation, bi-level optimization models are also proposed to determine the optimal allocation and operation of energy storage systems in [42] and of battery energy storage systems in [43], in which the upper level problem minimizes the storage system cost and the lower level problem implements the power flow in the network. Note that these works are based on cost minimization models and do not investigate the market interplay between storage, renewable generators and other players.

Assuming the storage firms as price taker players in the market, the optimal operation of storage firms in renewable integrated systems is determined by maximizing the profit from energy arbitrage and regulation services in [45], by maximizing the energy arbitrage profit in day-ahead and hour-ahead markets in [46], and by maximizing their energy and reserve profit in day-ahead and hour-ahead markets in [47]. Assuming the storage firms as price maker players in the market, the optimal charge/discharge operation of the storage devices, and the optimal operation and size of the storage devices are determined in [48] and [49], respectively, treating the price bids of market participants other than the storage players as exogenous inputs. The market operation behavior of all generation and storage firms are considered endogenously in a single-node electricity market in [24] using a Cournot-based electricity market model.

The charge/discharge behavior of storage firms and their impact on price volatility reduction in a multi-region electricity market model is studied in [52]. However, studying the joint effect of generation and storage on market price characteristics is missing in the literature. As we show in Chapter 6, wind might be more efficient than storage in reducing the average price and the results of [52] are not applicable when it is desirable to reduce the average price in the market. Therefore, different from the existing work, we consider the problem of managing the average price and the price volatility by optimal allocation of wind and storage capacities.

To the best of our knowledge, the problem of optimal allocation of wind and storage capacities for managing the average price and price volatility in the market has not been addressed before.

Literature on Research Question 5: Carbon Pricing Using Long-term Generation Expansion Models

Before electricity market deregulation, planning and operation scheduling were dependent on administrative and centralized procedures. Cost minimization models have been widely used in long-term capacity expansion models, e.g. planning in micro scale [53] and in macro scale [54]. During the last three decades, power industry in many countries and regions has transformed from being a centrally coordinated monopoly to a deregulated liberalized market. Although classical cost minimization and surplus maximization models do not incorporate strategic behaviors existing in the markets [1], [17], a heuristic cost minimization model is used for optimal investment planning in a competitive market assuming different forecasted market price scenarios [55]. Game-theoretic models including Cournot-Nash are capable of computing market equilibrium, price and generation, considering strategic behaviors. Cournot-based game models have been extensively used in energy systems analysis with formulations following the same logic, e.g. in electricity markets [18] and global oil markets [28].

Research on short and long-term capacity expansion in electricity markets using game-theoretic models has been conducted for a long time. Firms in the market compete by deciding on their generation quantities and expansion-planning decisions in a Cournot manner using an iterative solving algorithm [56] or a Mixed Linear Complementarity Problem [29]. Since solving the Cournot-based market games as a LCP could be cumbersome, the problem of computing the Nash Equilibrium (NE) is posed as a centralized optimization problem alternatively, e.g. on short term in [7] and on long-term in [19] and [23].

Cournot-based models used in electricity market representation are mostly deterministic. By considering a set of scenarios, uncertainty on the conjectured price responses, i.e., the slope of the linear inverse demand function, has been introduced in an oligopoly Bayesian game where generation companies decide on their long-term generation and capacity investment [32]. Uncertainties on both sides of supply and demand are considered in an oligopoly model in [57]. The load uncertainty is due to errors in the load forecast, and the generator availability uncertainty is about generators that might have a forced outage.

In both optimization and game-theoretic formulations, maximum carbon production can be embedded in the model as a constraint [54], the dual variable of which indicates the carbon price. In a cost minimization model, different values for maximum carbon production limit calculates different dual variables or carbon prices.

To the best of our knowledge, the problem of designing carbon price policies required to achieve long-term carbon cap targets in competitive electricity markets with strategic generation players has not been addressed before.

Literature on Research Question 6: Designing Tax&Subsidy Policies Using Long-term Market Expansion Models

The problem of electricity market expansion for studying the future generation mix or the CO_2 emission abatement has been studied in [54,58–64], with least cost generation expansion planning models, and in [19,23,29,32,33,65–67], with imperfectly competitive market evolution models. However, the electricity market expansion problem with emission and fast response dispatchable capacity incentive policies has not been investigated in the literature.

A least cost electricity generation expansion planning model, in which the total technology and operation costs to meet a specified demand are minimized, is studied in [58] considering the demand side management, and in [59] considering the simultaneous expansion of the electricity and gas networks. A multi-period power generation expansion model considering the CO_2 emission target constraint is developed in [54, 60], which calculates the additional costs of achieving a CO_2 abatement target as the absolute and marginal costs of abatement. Instead of embedding an emission target constraint, the cost of CO_2 emission is added to the fuel cost as carbon tax to support more renewable power installation in [61].

Considering a target penetration level for renewables and an ensured payback period constraints, the incentive rate (subsidy) on new renewable technologies are calculated in [62]. Incentive policies for renewable energies and emission reduction are also calculated using bilevel optimization models. Minimizing the total technology installation and operation costs in the lower level problem in [63] (or maximizing the social welfare in the lower level problem in [64]), the total policy intervention is minimized in the upper level problem to calculate the incentive policies of renewable subsidization or carbon taxation.

In order to investigate the strategic (price making) behavior of market participants, game-theoretical Cournot-based (oligopolistic) generation expansion models, i.e., market evolution models, are developed, for instance in [29], and are compared with least cost generation expansion models in [65]. Stochastic strategic generation expansion models are developed to include the uncertainty in conjectured-price response in [32] and the uncertainty in renewable power availability in [66]. Moreover, strategic generation expansion models have been utilized to manage the CO_2 emission level in the market, with an exogenous emission permit price in [67], and with a target emission constraint in

[19, 33]. It is discussed in [33] that the dual variable of the emission target constraint can be interpreted as the carbon price in the market.

The electricity market expansion models are also required to ensure that there is enough dispatchable capacity connected to the network. In order to support more investment on dispatchable capacity, the total generation from wind and solar is limited to 30% of aggregated annual generation in each region in [54], and to incentivize the right level of dispatchable capacity investment, capacity market is designed beside the energy market in [23]. The *Blueprint for the Future* report [68] suggests to limit the total VRE generation to a proportion of dispatchable generation in Australia in order to ensure the system reliability and minimum required dispatchable capacity.

To the best of our knowledge, the problem of designing emission taxation and fast response capacity support policies required to achieve long-term emission intensity reduction and dispatchability provision targets in competitive electricity markets with strategic generation, storage and transmission players has not been addressed before.

1.4 Thesis Contributions

The contributions of this thesis to answer the research questions discussed are as following:

- Contributions to answer Research Question 1 (in Chapter 2):
  - A classical Cournot-based model of wholesale electricity markets is theoretically extended to embed storage firms as strategic players in the market.
  - The game-theoretic game with strategic storage firms is developed and solved as a centralized optimization problem. The Centralized version can be developed for Cournot-based game models which have linear inverse demand functions.
- Contributions to answer Research Question 2 (in Chapter 3 and Chapter 4):
  - A Cournot-based multi-region electricity market model with nonlinear inverse demand functions is developed as a Mixed Complementarity Problem (MCP)

to find the impact of a coal power plant closure on electricity prices. In this model, generators are strategic and transmission lines are regulated.

  – Transmission lines are modeled as individual market participants likewise the other players in the game. In our model, we have strategic generation firms and regulated transmission lines.

- Contributions to answer Research Question 3 (in Chapter 5):

  – A bi-level optimization model is developed to find the optimal storage capacity required to limit the price volatility level in a multi-region electricity market.

  – The total storage capacity is minimized subject to a price volatility target constraint, in the upper level problem.

  – The strategic interaction between generation, transmission and storage players in the market is modeled as a stochastic (Bayesian) Cournot-based game with exponential inverse demand functions, in the lower level problem.

  – The existence of Bayesian Nash Equilibrium (Bayes-NE) is established for the lower level problem, which includes exponential inverse demand functions.

- Contributions to answer Research Question 4 (in Chapter 6):

  – A bi-level optimization model is developed to allocate a fixed budget optimally between regulated wind and storage capacities to minimize the weighted sum of average price and price volatility in an electricity market.

  – In the upper level problem, the weighted sum of average price and price volatility is minimized by allocating the fixed budget on regulated wind and storage capacities in the market.

  – In the lower level problem, the non-cooperative interaction between strategic and regulated generation, storage and transmission players in the market is modeled as a stochastic (Bayesian) Cournot-based game.

- Contributions to answer Research Question 5 (in Chapter 7):

  - A stochastic game-theoretic Cournot-based model is developed, in which strategic and regulated generation firms decide on expanding their generation capacity considering an emission constraint and the uncertainties due to intermittency of wind and solar.
  - The dual variable of the emission cap constraint at the Bayes-NE point of the game is used to calculate the carbon price required to limit the CO_2 emission to the cap level in the market.
  - The remaining value of new technologies (their value at the end of the study time) and the capacity retirement are considered in our model, which enables us to calculate the capacity expansion/closure during the study period.

- Contributions to answer Research Question 6 (in Chapter 8):
  - A game-theoretical Cournot-based electricity market expansion model is developed to find the future capacity mix of generation, storage and transmission in the market with both strategic and perfectly competitive (regulated) players.
  - All players in our model are subject to the emission intensity reduction constraint, the dual variable of which at the NE point is used to calculate the emission tax and subsidy that generators pay and receive for a targeted low emission market.
  - All players in our model are also subject to the fast response dispatchable generation constraint, the dual variable of which at the NE point is used to calculate the capacity tax and subsidy that generators and storage firms pay and receive for maintaining the system reliability (generation and demand balance).

1.5 Thesis Outline

Chapter 2: Game-theoretic Cournot-based Electricity Market Models with Storage

In Chapter 2, the mathematical formulation of a game-theoretic Cournot-based electricity market model is described. The market model includes several strategic and regulated generation firms and is extended as a multi-region model with strategic storage players. After describing the mathematical formulations of AC and DC power flows, the Cournot game in a wholesale electricity market is defined. The game is extended to include strategic storage players and is solved as a centralized optimization problem. Solving the game based on its Karush Kuhn Tucker (KKT) equations is also discussed in this chapter.

Chapter 3: NEM as the Case Study

In Chapter 3, we introduce the NEM market briefly and explain its pricing mechanism. The market clearing engine that settles the electricity generation, demand, and price is discussed. Moreover, we discuss the price and demand curves in competitive electricity markets based on linear and non-liner relations, and explain the calibration mechanism of the inverse demand functions based on historical price and demand data in the market. Then we show how accurate our model can simulate the electricity price and demand levels in NEM.

Chapter 4: Impact of a Coal Power Plant Closure on a Multi-region Wholesale Electricity Market

In Chapter 4, the system model of a wholesale electricity market including strategic/regulated generation, and transmission players is developed using a Cournot-based electricity market model. Regarding the nonlinear inverse demand functions, the set of KKT equations of market participants, i.e., wind and synchronous generators and transmission players, is solved to find the NE solutions. Market simulation is repeated with 365 different scenarios to calculate the price volatility in the market. The NEM market is studied as the case study and the impact of closing the Hazelwood power plant in Victoria on the market prices and volatility is investigated. Greenhouse gas emission of CO_2 in coal and gas power plants is also compared in simulations before and after the closure.

Chapter 5: Impact of Optimal Storage Allocation on Price Volatility in Electricity Markets

In Chapter 5, a bi-level optimization model is proposed to find the nodal storage capacities in an electricity market required to achieve a certain level of price volatility. The price volatility is calculated at the Bayes-NE solution of a stochastic Cournot-based electricity market model including wind and synchronous generators, storage firms, and transmission players. The set of KKT equations is solved to find the Bayes-NE solution of the stochastic game and a greedy algorithm is used to solve the upper and lower level problems. The NEM market is studied as the case study and the optimal capacity of storage in South Australia and Victoria respect to a certain level of price volatility is calculated. Our storage allocation framework is also applied to manage the price volatility in a 30-bus IEEE system.

Chapter 6: Regulated Wind/Storage to Reduce the Electricity Market Price and Volatility

In Chapter 6, a bi-level optimization model is proposed to allocate a fixed budget on regulated storage and wind capacities in order to minimize the weighted sum of average price and price volatility in a competitive market. A stochastic Cournot-based wholesale electricity market model is developed to find the Bayes-NE solution of the game between intermittent and synchronous generators, storage firms, transmission lines, and regulated wind and storage firm in the market. The set of KKT equations is solved to find the market equilibrium solution and a line search algorithm is used to solve the upper and lower level problems. The NEM market is studied as the case study and the optimal capacity for regulated wind and storage firm is calculated to minimize the weighted sum of price and volatility in the market.

Chapter 7: Long-Term Stochastic Planning in Electricity Markets Under Carbon Cap Constraint

In Chapter 7, a long-term stochastic Cournot-based generation expansion model is proposed, in which any generation firm maximizes the net present value of its profit subject to a aggregated CO_2 emission constraint. The dual variable of the emission constraint at the Bayes-NE point is used to calculate the carbon price required to limit the emission in the market. Regarding the linear inverse demand functions, the game model is solved as a centralized optimization problem. A generic wholesale electricity market including coal, gas and wind generators is studied as the case study under several wind availability scenarios. The effect of wind intermittency on capacity expansion decisions and on carbon price is discussed in the simulations.

Chapter 8: Designing Tax&Subsidy Incentives Towards a Green and Reliable Electricity Market

In Chapter 8, a long-term Cournot-based market expansion model is proposed, in which any generation, storage, and transmission firm maximizes the net present value of its profit subject to an upper bound on CO_2 emission intensity constraint and a fast response dispatchable capacity constraint. The dual variable of the emission constraint at the NE point is used to calculate the tax and subsidy incentive policies required to reduce the emission intensity and the dual variable of the dispatchable capacity at the NE point is used to calculate the tax and subsidy policies required to ensure the existence of adequate dispatchable capacity in an electricity market with high level of intermittent generation. The set of KKT equations are analyzed to calculate the tax and subsidy policies. The NEM market is considered as the case study and the required tax and subsidy policies are calculated to enable the transition towards a green and reliable electricity market by 2052 in Australia.

1.6 Publications

The outcomes of this thesis are published or under review for publication in the following journals and conferences.

- Journals:
  - Masoumzadeh, A., Nekouei, E., Alpcan, T., & Chattopadhyay, D. (2017). Impact of Optimal Storage Allocation on Price Volatility in Energy-only Electricity Markets. IEEE Transactions on Power Systems, vol. PP, no. 99, pp. 1-1, 2017. (Chapter 5)
  - Masoumzadeh, A., Nekouei, E., & Alpcan, T. Regulated Wind-Storage Allocation to Reduce the Electricity Market Price and Volatility, submitted to IEEE Transactions on Power Systems. (Chapter 6)
  - Masoumzadeh, A., Alpcan, T., & Nekouei, E. Designing Incentive Policies Towards a Green and Reliable Electricity Market, submitted to IEEE Transactions

on Power Systems. (Chapter 8)

- Conferences:
  - Masoumzadeh, A., Nekouei, E., & Alpcan, T. (2017, September). Impact of a Coal Power Plant Closure on a Multi-region Wholesale Electricity Market. in 2017 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), Sept 2017, pp. 16. (Chapter 4)
  - Masoumzadeh, A., Nekouei, E., & Alpcan, T. (2016, November). Long-term Stochastic Planning in Electricity Markets under Carbon Cap Constraint: A Bayesian Game Approach. In Innovative Smart Grid Technologies-Asia (ISGT-Asia), 2016 IEEE (pp. 466-471). IEEE. (Chapter 7)

Part I

Electricity Market Models and NEM as the Case Study

Introduction to Part I

ELECTRICITY market models are developed to find the electricity market prices based on the interaction between market players. Classical electricity market models just include generation players, who aim to maximize their profit considering the transmission constraints in the network. The classical electricity market models are extended in this thesis because of the integration of storage firms, in small or large scales.

In Chapter 2, we introduce a classical Cournot-based electricity market model, in which we discuss the generation and transmission players explicitly. We extend the model by embedding the storage firms as strategic players in the market. The impact of storage energy flow on market prices is compared in charging and discharging situations. This electricity market model is used as part of the models in other chapters.

In Chapter 3, we first introduce the NEM market as the case study for our simulations in this thesis and explain how the market clearing engine settles the electricity generation, demand and price in the NEM. Then, we explain the inverse demand function calibration methodology, and compare the linear and non-linear inverse demand functions with each other. We also show how accurate our model can simulate the electricity price and demand levels in NEM.

Chapter 2

Game-theoretic Cournot-based Electricity Market Models with Storage

Existing wholesale electricity markets have been designed for the traditional electricity grid that has very limited storage capability. In the near future, a substantial amount of storage capacity is expected to be installed in power grids following the decentralization and renewable distributed generation trends. At the same time, information and communication technologies enable aggregation of storage capabilities regardless of their specific form which can be, e.g. pump-storage hydro, large-scale or distributed residential batteries, or electric vehicles. In this chapter, a classical Cournot game model is extended in order to analyze how strategic storage firms can be modeled in an electricity market and influence the wholesale price levels during charging and discharging periods. The developed model takes power generators (synchronous and intermittent), storage firms and transmission lines as market players into account, and is used as part of the developed models in the other chapters.

2.1 Introduction

In this chapter, a classical Cournot-based electricity market model is extended by embedding strategic storage firms which can be considered as owners of virtual power plants. Our model considers synchronous and renewable generators, storage firms and transmission lines in a multi-region electricity market. Any player maximizes its utility in the game, assuming linear price (inverse demand) functions. Note that the solution of individual players' profit maximization problems, the Nash Equilibrium solution of the game, can be found by solving a single optimization problem or a Mixed Complementarity Problem (MCP). Because the inverse demand functions in our model are linear, we can model the electricity market as a centralized optimization problem.

The **contributions** of this chapter include the following:

- We theoretically extend a classical multi-period Cournot-based electricity market model by introducing storage firms, who own virtual power plants, as strategic players in the market.

- We solve our extended Cournot-based electricity market model as a centralized optimization problem. Note that the centralized version just applies to market models with linear inverse demand functions.

The rest of this chapter presents the AC and DC power flow models in Section 2.2, the wholesale electricity market game model in Section 2.3, and ends with a conclusion in Section 2.5.

2.2 Mathematical Model Description

AC Power Flow

Power flow equations (2.1) describe the steady-state behavior in an electric power grid. At point or bus i, the nominal power injected to the network, S_i^{nominal}, consists of active power, P_i^{active}, and reactive power, Q_i^{reactive}. The voltage level at bus i, V_i, and the current injected to the network from the bus i, I_i, are as:

$$S_i^{\text{nominal}} = P_i^{\text{active}} + jQ_i^{\text{reactive}} = V_i I_i^* \quad \forall i \tag{2.1}$$

$$P_i^{\text{active}} - jQ_i^{\text{reactive}} = V_i^* I_i = V_i^* \sum_j Y_{ij} V_j, \quad \forall i, \tag{2.2}$$

where Y_{ij} denotes the admittance between bus i and j, and $(.)^*$ denotes complex conjugation.

Accordingly, the active and reactive powers correspond to the real and imaginary parts of the nominal power, respectively, as:

$$P_i^{\text{active}} = Re\{V_i^* \sum_j Y_{ij} V_j\} \quad \forall i$$
$$Q_i^{\text{reactive}} = -Im\{V_i^* \sum_j Y_{ij} V_j\} \quad \forall i$$

Considering the phasor type of the voltage V_i with the voltage absolute $|V_i|$ and the voltage phase δ_i as $V_i = |V_i|e^{j\delta_i}$, and the admittance elements Y with their conductance amounts G and susceptance amounts B as $Y_{ij} = G_{ij} + jB_{ij}$, we can write the final power flow equations as:

$$P_i^{\text{active}} = \sum_j |V_i||V_j|(G_{ij} cos\delta_{ij} + B_{ij} sin\delta_{ij}), \quad \forall i,$$
$$Q_i^{\text{reactive}} = \sum_j |V_i||V_j|(G_{ij} sin\delta_{ij} - B_{ij} cos\delta_{ij}), \quad \forall i,$$

where δ_{ij} denotes $\delta_i - \delta_j$.

DC Power Flow

Direct Current Load Flow (DCLF) provides estimates of line power flows on AC power systems. As a simplification, DCLF looks only at the active power and neglects the reactive power [69].

DC load flow analysis has four basic assumptions:

- Line resistances (active power losses) are negligible i.e. in line impedance Z we assume that $\mathrm{Re}(Z) \ll \mathrm{Im}(Z)$.
- Voltage angle differences are assumed to be small i.e. $\sin(\delta) \simeq \delta$ and $\cos(\delta) \simeq 1$.
- Magnitudes of bus voltages are set to 1.0 per unit (flat voltage profile, V_{rated}).

With the simplified AC power equations under the assumptions made above, the active power flowing from node i to node j can be shown as:

$$
\begin{aligned}
P_{ji}^{\text{tr}} &= |V_i|(G_{ij}|V_i| - G_{ij}|V_j|\cos\delta_{ij} - B_{ij}|V_j|\sin\delta_{ij}) \\
&\simeq |V_{rated}|^2(-B_{ij}\delta_{ij}) \quad \forall i, j
\end{aligned}
\tag{2.3}
$$

which is used in our developed electricity market model to show the power flow on interconnectors.

Note that we rename the active power P^{active} to q in the remainder of Chapter 2.

2.3 Game-theoretic Model of a Wholesale Electricity Market

Power suppliers in a competitive electricity market generate power in order to maximize their profits. Players in a generic strategic (non-cooperative) game are either able to affect the price by deciding on their generation quantities, which are referred to as strategic players, or just follow the price in the market, which are referred to as perfectly competitive (price-taking) players. Accordingly, we define the following Cournot-based game to model the electricity generation behavior in a wholesale electricity market.

2.3.1 Game Definition and Nash Equilibrium:

Let $\mathcal{K} = \{1, \cdots, K\}$ be the set of generation firms participating in the electricity market. At time $t \in \mathcal{T}$, $\mathcal{T} = [1, \cdots, T]$, they decide on their electricity generation $q_t^{\text{g}} = [q_{1,t}^{\text{g}}, \cdots, q_{K,t}^{\text{g}}] \succcurlyeq 0$. We assume that the generator k has constant marginal cost of production $c_k \geq 0$.

The price P determines per unit revenue of a firm in the market. Inverse demand or pricing function, $P_t(D_t)$, is defined by a linear equation with parameters α_t and β_t, and is determined by the market demand, D_t, that has to match the total generation, $\sum_k q_{k,t}^{\text{g}}$, in a one-node model:

$$
P_t(D_t) = \alpha_t - \beta_t D_t. \tag{2.4}
$$

The demand function parameters α and β are calculated based on the historical price and demand data in the region.

Players in the model are categorized into perfectly competitive and strategic ones, which differ in their objective functions. A strategic player (generator) decides on its generation $q^g_{k,t}$ according to the following objective function:

$$U^g_k = \sum_t q^g_{k,t} P_t(D_t) - c_k q^g_{k,t}. \tag{2.5}$$

while the perfectly competitive or regulated generator's objective function is:

$$U^g_k = \sum_t q^g_{k,t} P_t(D_t) + \beta_t q^g_{k,t} - c_k q^g_{k,t} \tag{2.6}$$

Due to the term $\beta_t q^g_{k,t}$, the perfectly competitive player never withholds its available capacity to raise the market price, i.e. it does not have or misuse the market power ability to strategically increase the wholesale prices.

Definition 1. *A perfectly competitive (PC) player does not misuse or have the market power to raise wholesale prices, while a strategic player may deliberately decide to increase the prices by withholding its available capacity.*

Considering all firms strategic, the generation firm k solves the following profit maximization problem:

$$\max_{q^g_{k,t} \geq 0} U^g_k(q^g) := \sum_t q^g_{k,t} P_t(q^g_t) - c_k q^g_{k,t} \quad s.t. \quad A^g q^g \leq b^g \tag{2.7}$$

where generation constraints are embedded in the inequality $Aq^g \leq b$. The action space of the generation players is defined as $\Omega = \{q^g \in \mathbb{R}^{+^{K*T}} | A^g q^g \leq b^g\}$, which is compact, convex, and non-empty in our model. Moreover, as the quadratic objective function is concave and continuous on its action set, the problem (2.7) is a convex optimization problem.

The problem (2.7) has the corresponding Lagrangian function,

$$L_k = \sum_t (\alpha_t - \beta_t \sum_{k'} q^g_{k',t}) q^g_{k,t} - c_k q^g_{k,t} - \lambda(A^g q^g - b^g),$$

where $\lambda \geq 0$ is the vector of Lagrange multipliers.

Consequently, the Karush-Kuhn-Tucker conditions are both necessary and sufficient for optimality [70],

$$\frac{dL_k}{dq^g_{k,t}} = \alpha_t - \beta_t \sum_{k'} q^g_{k',t} - \beta_t q^g_{k,t} - c_k - \lambda a(k*t) = 0, \tag{2.8}$$

where $a(k*t)$ is the $(k*t)^{th}$ column of the constraint matrix A^g. The solution of (2.8) is the best response of player or generation firm k given the decisions of other players. The intersection of the best responses of all players, q^{g*}, is by definition the NE of the corresponding strategic game $\mathcal{G} = \{\mathcal{K}, q^g \in \Omega, U^g\}$.

Proposition 1. *The electricity generation strategic game $\mathcal{G} = \{\mathcal{K}, q^g \in \Omega, U^g\}$ played among the set of $\mathcal{K}$ firms, which decide on generation levels q^G in order to maximize the profit U^g admits a Nash Equilibrium solution q^{g*} if the action space $\Omega = \{q^g \in \mathbb{R}^{+^{K*T}} | A^g q^g \leq b^g\}$ given coefficient matrix A^g and vector matrix b^g is convex, compact, and non-empty. Furthermore, any solution q^{G*} of the quadratic optimization problem*

$$\max_{q^g \geq 0} F := \sum_{k,t} (\alpha_t - \frac{\beta_t}{2} \sum_{k'} q^g_{k',t}) q^g_{k,t} - \frac{\beta_t}{2} (q^g_{k,t})^2 - c_k q^g_{k,t}$$
$$s.t. \quad A^g q^g \leq b^g$$

is a NE of the game.

Proof. The proof follows the Theorem 4.4 in [7] and [71].

2.3.2 The Game with Strategic Storage Firms

We call a firm that operates a set of storage capacities, e.g. battery or pump-storage hydro, in the network a *storage firm*. The firm's operation mode can be either charging or discharging. While charging, the storage generates electricity similar to the conventional generators, and while discharging, it operates as an additional load in the system. Having generation (Discharging) and demand (charging) modes, a storage firm does not look like conventional generators modeled in the market.

A strategic storage player with decision variable q_t^{st} is modeled and embedded in our non-cooperative electricity generation game. Storage facilities are limited by their *charging rate* and *capacity* constraints [72]. According to the charging rate constraint, discharging takes positive values $0 \leq q_t^{\text{st}} \leq q^{\text{st,max}}$, and charging takes negative values $q^{\text{st,min}} \leq q_t^{\text{st}} \leq 0$. In order to satisfy the capacity constraints, the actual charging level, with initial value of $Q^{\text{st},0}$, must be maintained within a proper range, i.e., $0 \leq Q^{\text{st},0} - \sum_{t'=1}^{t} q_{t'}^{\text{st}} \leq Q^{\text{st,max}}$, where $t \in \mathcal{T}$.

While discharging, the storage firm injects electricity into the grid. Therefore, its discharging adds to total generation, which is equal to the total demand: $y_t = \sum_k q_{k,t}^{\text{g}} + q_t^{\text{st}}$, if $q_t^{\text{st}} \geq 0$. Given the inverse demand function in (2.4), the utility function of the storage firm, $U_t^{\text{st}} = P_t q_t^{\text{st}}$, becomes:

$$U_t^{\text{st}} = (\alpha_t - \beta_t(\sum_k q_{k,t}^{\text{g}} + q_t^{\text{st}}))q_t^{\text{st}} \quad if \quad q_t^{\text{st}} \geq 0 \tag{2.9}$$

On the other hand, storage charging results in changing the intercept coefficient in the inverse demand function, i.e., $P_t = (\alpha_t - \beta_t q_t^{\text{st}}) - \beta_t D_t$, if $q_t^{\text{st}} < 0$. While charging, given the total generation of incumbent generators, $\sum_k q_{k,t}^{\text{g}}$, the utility function of the storage firm, $U_t^{\text{st}} = P_t q_t^{\text{st}}$, considering the new inverse demand function is:

$$U_t^{\text{st}} = ((\alpha_t - \beta_t q_t^{\text{st}}) - \beta_t \sum_k q_{k,t}^{\text{g}})q_t^{\text{st}} \quad \text{if} \quad q_t^{\text{st}} < 0. \tag{2.10}$$

Note that the terms in these utility functions are identical and instead of looking at a storage firm in discharging and charging modes, we can consider the strategic storage firm in a non-cooperative electricity generation game as a generator with both positive and negative bids (generation).

Therefore, it is acceptable to assume a storage firm as a generator with real decision variable, i.e., a generator capable of generating both positive and negative amounts. Figure 2.1 illustrates how storage charging/discharging affects the supply curve, while the demand curve is assumed fixed, and shifts the equilibrium point.

Due to extension of the game for multiple strategic storage players, the objective func-

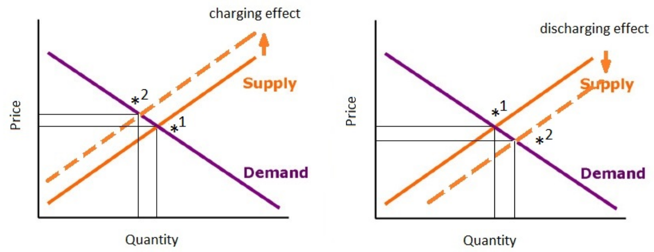

Figure 2.1: Storage charging and discharging effects on supply/demand equilibrium point at a given moment in time (points 1 and 2 represent equilibrium point before and after storage installation).

tion of storage firm b and generator firm k respectively become:

$$U_b^{\mathrm{st}}(q^{\mathrm{g}}, q^{\mathrm{st}}) = \sum_t q_{b,t}^{\mathrm{st}}(\alpha_t - \beta_t(\sum_k q_{k,t}^{\mathrm{g}} + \sum_b q_{b,t}^{\mathrm{st}})) \tag{2.11}$$

$$U_k^{\mathrm{g}}(q^{\mathrm{g}}, q^{\mathrm{st}}) = \sum_t q_{k,t}^{\mathrm{g}}(\alpha_t - \beta_t(\sum_k q_{k,t}^{\mathrm{g}} + \sum_b q_{b,t}^{\mathrm{st}})) - c_k q_{k,t}^{\mathrm{g}} \tag{2.12}$$

Consequently, the NE point of the new game including strategic storage players can be computed by solving the modified centralized optimization problem:

$$\max \sum_t (\alpha_t - \frac{\beta_t}{2}(\sum_k q_{k,t}^{\mathrm{g}} + \sum_b q_{b,t}^{\mathrm{st}}))(\sum_k q_{k,t}^{\mathrm{g}} + \sum_b q_{b,t}^{\mathrm{st}}) - \frac{\beta_t}{2}(\sum_k {q_{k,t}^{\mathrm{g}}}^2 + \sum_b {q_{b,t}^{\mathrm{st}}}^2) - \sum_k c_k q_{k,t}^{\mathrm{g}} \tag{2.13}$$

$$s.t. \quad [\; A^{\mathrm{g}} \quad A^{\mathrm{st}} \;][\; \begin{matrix} q^{\mathrm{g}} \\ q^{\mathrm{st}} \end{matrix} \;] \leq [\; \begin{matrix} b^{\mathrm{g}} \\ b^{\mathrm{st}} \end{matrix} \;]$$

Based on the results in Proposition (1), the Lagrangian equations for the optimization problem (2.13) respect to variables q^{g} and q^{st} coincidence with Lagrangian equations for individual profit maximization problems of storage firms with utility function (2.11) and generators with utility function (2.12). Hence, the solution of (2.13) coincides with the NE of the game.

In order to consider energy flow efficiency for charging and discharging, $0 \leq \mu^{\mathrm{dis}}, \mu^{\mathrm{ch}} \leq 1$, it needs to allocate two independent positive variables $q_{b,t}^{\mathrm{ch}}$ and $q_{b,t}^{\mathrm{dis}}$ for storage charge and discharge quantities. Again, the net energy flow of storage firm b at time t, $q_{b,t}^{\mathrm{st}} =$

$q^{\mathrm{dis}}_{b,t}\mu^{\mathrm{dis}} - \frac{q^{\mathrm{ch}}_{b,t}}{\mu^{\mathrm{ch}}}$, takes a real value. However, for simplicity we assume no energy loss for storage firms and continue only with the variable $q^{\mathrm{st}}_{b,t}$.

2.4 Multi-nodal, Multi-period Wholesale Electricity Market

2.4.1 The Game as a Centralized Optimization Problem

The multi-period (finite horizon) wholesale electricity market model presented can be extended at multiple interconnected nodes by inserting the node index $i \in \mathcal{I}, \mathcal{I} = [1, \cdots, I]$. In a multi-nodal game, the transmission value between the nodes i and j emerges as an independent variable $q^{\mathrm{tr}}_{ij,t}$ which needs to be decided on in the game. Given the transmission player between nodes i and j) behaves perfectly competitive, according to Definition (1) and similar to (2.6) it has the utility function:

$$U^{\mathrm{tr}}_{ij} = \sum_t (P_{i,t} - P_{j,t})q^{\mathrm{tr}}_{ij,t} + \frac{\beta_{j,t} + \beta_{i,t}}{2}(q^{\mathrm{tr}}_{ij,t})^2$$

where the player transmits electricity from the higher price node to the lower price node as long as either there is price difference between nodes i and j or the transmission line is congested. The second term, $\frac{\beta_{j,t}+\beta_{i,t}}{2}(q^{\mathrm{tr}}_{ij,t})^2$, differentiates the player from a strategic one and prevents withholding the available capacity to benefit strategically from the price difference between nodes.

On the other hand, when the transmission player between nodes i and j behaves strategically, similar to (2.5) it has the following utility function:

$$U^{\mathrm{tr}}_{ij,t} = \sum_t (P_{i,t} - P_{j,t})q^{\mathrm{tr}}_{ij,t}$$

where it is capable of increasing the price differences strategically by withholding its available capacity.

Players of the game are categorized into: (1) Generation firms, (2) Storage firms, (3) Transmission firms, which can be either strategic or regulated. The generation firm k in node i decides on the vector of variables $[q^{\mathrm{g}}_{k,i,1}, \cdots, q^{\mathrm{g}}_{k,i,T}]$ which take positive values, whereas the storage firm b in node i decides on the vector of variables $[q^{\mathrm{st}}_{b,i,1}, \cdots, q^{\mathrm{st}}_{b,i,T}]$ which take both positive and negative values, and the transmission firm between nodes i and j decides on the vector of variables $[q^{\mathrm{tr}}_{ij,1}, \cdots, q^{\mathrm{tr}}_{ij,T}]$ which take both positive and negative values as well.

The mathematical model presented below is an extension of the centralized optimization problem (2.13), which is developed for the energy-only five node NEM market subject to generation, storage and transmission constraints. The network constraints are given based on DC load flow (DCLF) assumptions (the Kirchoffs law is always respected in our models). The multi-nodal intertemporal wholesale electricity market model consisting of strategic generations and storage firms and regulated transmission lines is:

$$\max_{\substack{q^{\mathrm{g}}, q^{\mathrm{tr}}, \delta, D \succeq 0 \\ q^{\mathrm{st}}}} \sum_{i,t} (\alpha_{i,t} - \frac{\beta_{i,t}}{2} D_{i,t}) D_{i,t} - \sum_{k,i,t} c_{k,i} q^{\mathrm{g}}_{k,i,t} - (\sum_{k,i,t} \frac{\beta_{i,t}}{2} {q^{\mathrm{g}}_{k,i,t}}^2 + \sum_{b,i,t} \frac{\beta_{i,t}}{2} {q^{\mathrm{st}}_{b,i,t}}^2) \tag{2.14a}$$

$s.t.$

$$D_{i,t} = \sum_k q^{\mathrm{g}}_{k,i,t} + \sum_b q^{\mathrm{st}}_{b,i,t} - \sum_j q^{\mathrm{tr}}_{ji,t} \quad \forall i, t \tag{2.14b}$$

$$q^{\mathrm{tr}}_{ji,t} = |V_{rated}|^2 (-B_{ij} \delta_{ij,t}) \leq Q^{\mathrm{tr}}_{ji} \quad \forall i, j, t \tag{2.14c}$$

$$\delta_i^{\mathrm{min}} \leq \delta_{i,t} \leq \delta_i^{\mathrm{max}} \quad \forall i, t \tag{2.14d}$$

$$q^{\mathrm{g}}_{k,i,t} \leq Q^{\mathrm{g}}_{k,i} \quad \forall k, i, t \tag{2.14e}$$

$$q^{\mathrm{g}}_{k,i,t} - q^{\mathrm{g}}_{k,i,t-1} \leq R^{\mathrm{up}}_{k,i} Q^{\mathrm{g}}_{k,i} \quad \forall k, i, t \tag{2.14f}$$

$$q^{\mathrm{g}}_{k,i,t-1} - q^{\mathrm{g}}_{k,i,t} \leq R^{\mathrm{dn}}_{k,i} Q^{\mathrm{g}}_{k,i} \quad \forall k, i, t \tag{2.14g}$$

$$q^{\mathrm{g}}_{k,i,t} \leq \omega_{k,i,t} Q^{\mathrm{g}}_{k,i} \quad \forall k, i, t \tag{2.14h}$$

$$\sum_t q^{\mathrm{g}}_{k,i,t} \leq RA^{\mathrm{g}}_{k,i} \quad \forall k, i \tag{2.14i}$$

$$0 \leq Q^{\mathrm{st},0} - \sum_{t'=1}^{t} q^{\mathrm{st}}_{t'} \leq Q^{\mathrm{st}} \quad \forall b, i, t \tag{2.14j}$$

$$q^{\mathrm{st,min}}_{b,i} \leq q^{\mathrm{st}}_{b,i,t} \leq q^{\mathrm{st,max}}_{b,i} \quad \forall b, i, t \tag{2.14k}$$

where $q^{\mathrm{g}}, q^{\mathrm{st}}, q^{\mathrm{tr}}$ are independent variables, and $D_{i,t}, \delta_{ij,t}$ are intermediate variables.

The optimization problem (2.14a)-(2.14k) considers all individual profit maximization problems. As shown in Proposition 1, the objective function (2.14a) enables us to write the game as a centralized optimization problem. Constraint (2.14b) show the nodal electricity supply and demand balance. Constraint (2.14c) presents the electricity transmitted between nodes (where $|V_{rated}|$ is the rated voltage assumed in the network, B_{ij} is the susceptance characteristic of the line and δ_{ij}, i.e., $\delta_i - \delta_j$, is voltage phase difference between nodes i and j) and limits the transmission values to the maximum power flow capacities. As the problem is on DCLF format, constraint (2.14d) expresses the technical limit just on voltage phases and does not consider the voltage magnitudes. The generation capacity limit is shown in (2.14e). Constraints (2.14f)-(2.14g) show the ramp limits of generators while the problem is cast as a chronological one. Period-by-period availability limit applicable to all generators especially intermittent wind turbines are shown in (2.14h), and intertemporal generation limits due to fuel scarcity or planned/forced outages are expressed in (2.14i). Considering the strategic storage players, we include the constraints (2.14j)-(2.14k) to show the storage capacity and the charging rate limit, respectively.

2.4.2 The Game as a Mixed Complementarity Problem

Alternatively, we can solve the electricity market game using the best response functions of all firms participating in the market. The best response of any player satisfies the necessary and sufficient Karush-Kuhn-Tucker (KKT) conditions. The KKT conditions, i.e. the set of first order optimality equations of all players, are the derivative of Lagrangian function of each player L respect to all its decision variables, e.g. q:

$$\frac{\partial L}{\partial q} \leq 0 \;\perp\; q \geq 0 \text{ if } q \geq 0 \tag{2.15a}$$

$$\frac{\partial L}{\partial q} = 0 \text{ if } q \text{ is free} \tag{2.15b}$$

where the perpendicularity sign, $\perp$, indicates that one of the adjacent inequalities must at least be satisfied as an equality [73], i.e., the complementarity constraints.

Then, any intersection of all firms' best response functions will be a NE. At the NE strategy of the game, no player has any incentive to unilaterally deviate its strategy from the NE point. The KKT equations of the game are fully described in Chapter 5.

2.5 Conclusion

Electricity networks are transforming toward installing substantial amounts of storage in different forms of pump-hydro, large-scale batteries and distributed batteries as a buffer system to store the excess generated electricity at off-peak hours and sell it to network at peak hours. We developed a multi-region Cournot-based wholesale electricity market model and embedded the storage in it with the following conclusions:

- Storage players can be modeled as generators with both positive and negative generation amounts in the market. In other words, although storage charging impacts the inverse demand functions on the demand side, we can equivalently find the storage impact on the supply side.
- Transmission lines are also modeled as individual players in our model, who maximize their utility in the game. Considering a market power term, we have both strategic and regulated transmission players in our model.
- Given linear inverse demand functions in our Cournot-based electricity market model, we transform the game model into a centralized version and solve it as an optimization problem to find the NE solution.
- When there is a nonlinear inverse demand function in a Cournot-based market model, the best responses of all players must be written as the set of KKT equations to find the NE solution of the game.

The electricity market model developed in this chapter is used as part of the models in other chapters.

Chapter 3
NEM as the Case Study

3.1 Overview of National Electricity Market (NEM)

The Australia's National Electricity Market (NEM) operates as a wholesale market for the supply of electricity to retailers and end-users. NEM is operated by Australian Energy Market Operator (AEMO) and consists of five interconnected regions (states) shown in Fig. 3.1: South Australia (SA), Queensland (QLD), Tasmania (TAS), Victoria (VIC) and New South Wales (NSW).

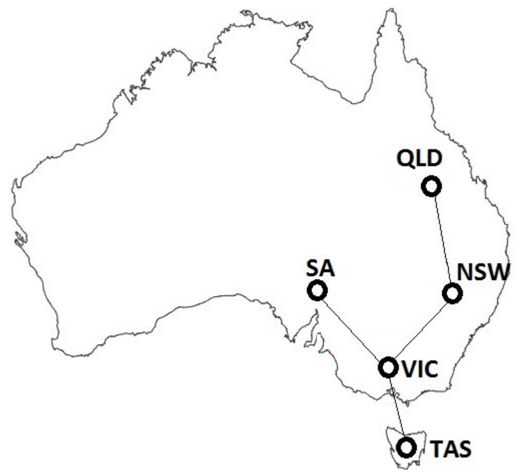

Figure 3.1: Interconnected states in Australia's National Electricity Market.

In NEM 2017, different types of electricity generation firms, i.e. coal, gas, hydro and wind, with a total (both dispatchable and intermittent) generation capacity of 45.7 GW are active. Roof-top solar with capacity of 4.8 GW is also generating electricity in Australia. Fig. 3.2 illustrates the existing generation capacities in the NEM, which are used in our numerical simulations and are gathered from AEMO's website (aemo.com.au).

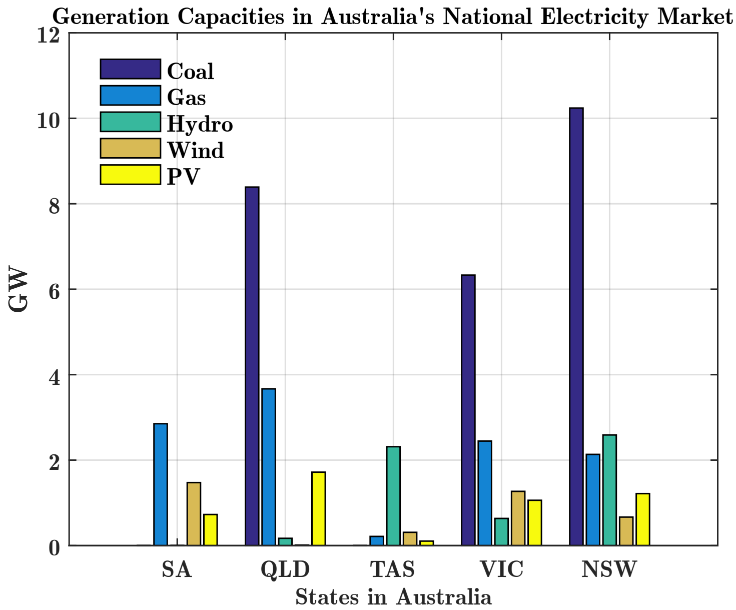

Figure 3.2: Dispatchable and intermittent electricity generation capacities in the NEM, 2017.

In market NEM, 13, 23, 21, 20, and 18 synchronous generators are participating in SA, QLD, TAS, VIC, and NSW, respectively. The NEM also includes the total wind power capacities of 1250 MW in SA, 0 MW in QLD, 250 MW in TAS, 964 MW in VIC, and 554 MW in NSW. The share of wind power installed capacity in total electricity generation capacity is 34.3% in SA, 0% in QLD, 9.1% in TAS, 8.7% in VIC, and 3.4% in NSW. SA possesses the highest share of wind power in its total electricity generation in NEM.

In the NEM, electricity is an ideal commodity which is exchanged between producers and consumers through a pool. Wholesale trading of electricity is conducted in a spot market. Generators offer to supply the market with specific amounts of electricity at particular prices. Offers are submitted every five minutes (market price cap is 11000 $/MWh and market floor price is -1000 $/MWh). Finally, the output from all generators is aggregated and scheduled to meet the demand.

Fig. 3.3 illustrates the clearing engine mechanism in the NEM. Bids to produce electricity received by AEMO are stacked for each dispatch period in ascending price order. Generators are scheduled into production to meet the demand with the least-cost generation option. Note that the spot price for each trading period (half hour) is calculated as the average of the six dispatch prices (every five minutes).

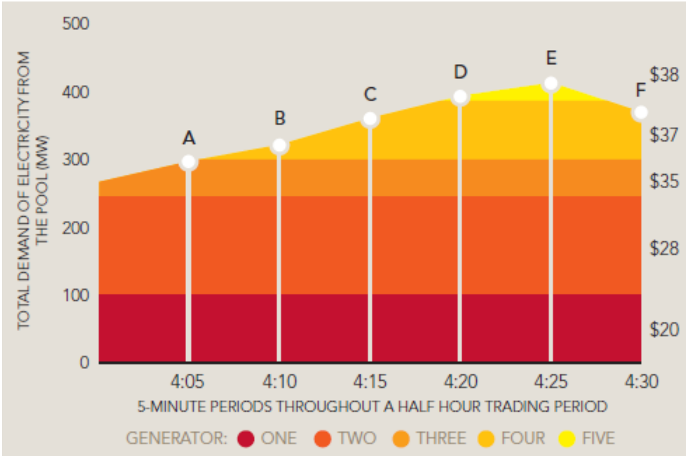

Figure 3.3: The clearing engine mechanism in the NEM (Source: AEMO).

Electricity trade between two regions helps to lower the price difference between those regions. The interconnectors in NEM are either regulated or unregulated. Regulated interconnectors have passed the Australian Competition and Consumer Comission (ACCC) devised regulatory test and are eligible to receive fixed annual revenue, but unregulated ones derive revenue by trading in the spot market. All interconnectors in NEM are regulated, while Tasmania is connected via an unregulated interconnector to Victoria. The inteconnetor capacities existing in NEM are listed in Table C.4 in Appendix C.

3.2 Calibrating the Inverse Demand Functions

In economic theory, price relates to demand in a function called the demand curve. In this thesis, We have calibrated the inverse demand curves based on NEM's historical price and demand data with both linear and non-linear functions.

Two most commonly used inverse demand functions in microeconomics literature are the linear and iso-elastic models [74], e.g., in [24, 28]. Exponential inverse demand function has also been used in energy market models [75]. The inverse demand function of most commodities follows a non-linear downward sloping price versus demand relation [76] and a linear inverse demand function is just its first order approximation at an operating price and demand level. The linear function may become invalid when the operating point changes drastically, e.g., when the price plunges from the very high amount of 11000 \$/MWh to low level of 50 \$/MWh.

The iso-elastic and exponential functions can more accurately illustrate the price and demand relation. In fact, the exponential function, $p = \alpha' e^{-\beta' q}$, is the modified version of the iso-elastic function, $\ln(p) = \alpha - \beta \ln(q)$ or $p = \tilde{\alpha} e^{-\beta \ln(q)}$ with $\tilde{\alpha} = e^{\alpha}$, which substitutes the logarithmic demand levels with nominal levels. We discuss three reasons privileging the exponential inverse demand function over the iso-elastic. Firstly, the KKT conditions (first order optimality conditions) of our developed market game models become highly non-linear under the iso-elatsic function and it becomes hard to numerically solve them. The derivative of the exponential inverse demand function with respect to demand is $\frac{\partial p}{\partial q} = -\beta' p$, while the derivative of the iso-elastic function respect to demand is $\frac{\partial p}{\partial q} = -\beta p q^{-1}$. Secondly, the exponential function has a finite price feature while the iso-elastic function goes to infinity for small levels of demand. Lastly, the exponential function partially covers the specifications of both linear and iso-elastic functions. Consequently, we use and calibrate exponential inverse demand functions to characterize the price and demand relations in our models in Chapters 4, 5 and 6.

In electricity market models, the constant coefficients in the inverse demand functions are usually calibrated based on actual price/demand data , p/q, and price elasticity levels, $\epsilon = \frac{\frac{\partial q}{q}}{\frac{\partial p}{p}}$ [76], which are given as input to our models. Given two equations of price-demand function and elasticity function, i.e., $p = f(q)$ and $\epsilon = \frac{\partial q}{\partial p} \frac{p}{q}$, and two unknowns, we can find the both parameters in all three discussed inverse demand functions. For instance, given the price of $p = 50$ \$/MWh, demand of $q = 1500$ MW and price elasticity of demand $\epsilon = -0.3$, the linear function $p = \frac{650}{3} - \frac{1}{9} q$, the iso-elastic function $\ln(p) = 28.28 - \frac{10}{3} \ln(q)$, and the exponential function $p = 50 e^{\frac{10}{3}} e^{-\frac{1}{450} q}$ can be extracted. Fig. 3.4 compares the calibrated linear, exponential and iso-elastic inverse demand functions. The properties of the exponential function lie between the linear and iso-elastic functions.

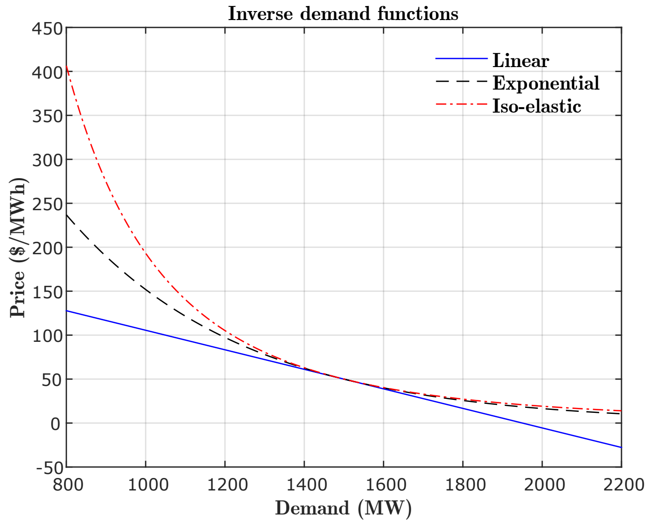

Figure 3.4: Calibrated linear, exponential and iso-elastic inverse demand functions at price 50 $/MWh, demand 1500 MW, and elasticity -0.3.

3.3 Model Calibration with Real Data

In our simulations, we use the technical and financial data on the generation, storage, and transmission technologies in the NEM (Appendix C), and run our model which is calibrated with historical data in the market. Moreover, the inverse demand functions (the relation between price and demand in the market) in our wholesale electricity market models are calibrated with real data, as explained in Section 3.2.

As an example, the simulation results of our model for hourly price and demand are compared with the historical data for the average day of 2017 in Fig. 3.5. It can be seen that the price and demand levels are calculated with the error terms of 6.4% and 4.7%, respectively.

Note that the NEM market with the assumptions explained is considered as the case study throughout the whole thesis. Furthermore, we use the non-linear inverse demand function in Chapters 4, 5 and 6, and use the linear inverse demand function in the electricity market models developed in Chapters 7 and 8.

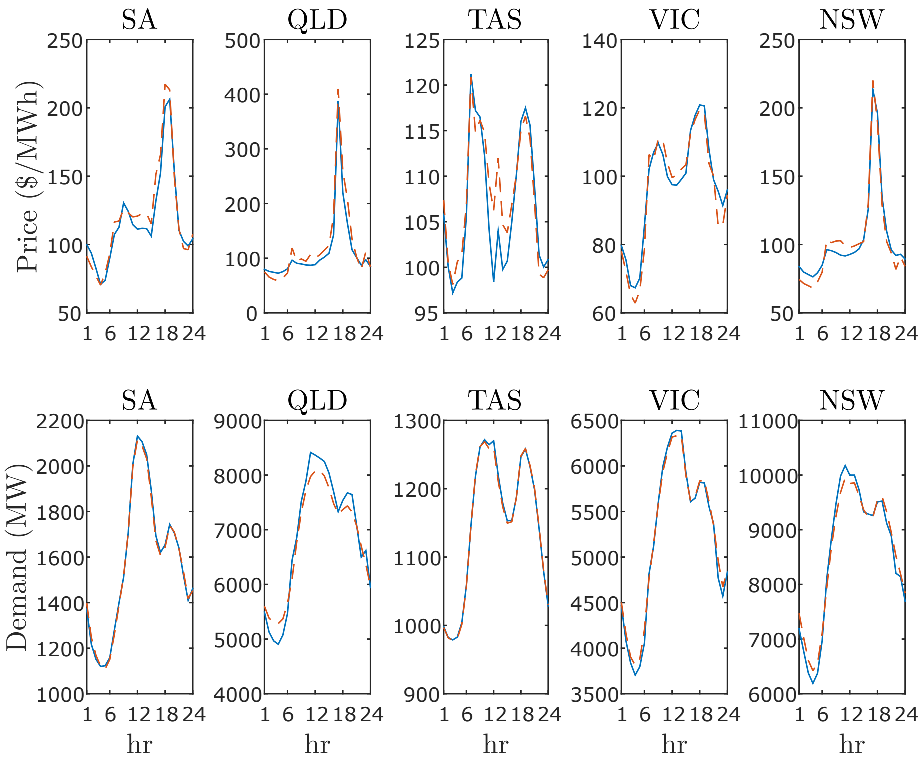

Figure 3.5: Comparing the simulation results (solid lines) of hourly price and demand with the historical data (dashed lines) (Source: AEMO) for the average day of 2017 in five states of the NEM.

Part II

Analysis of Price Volatility in Electricity Markets

Introduction to Part II

AFTER introducing the Cournot-based electricity market models and embedding storage firms in those models in Chapter 2, we extend the developed models and apply them to analyze the price level and price volatility in electricity markets.

In Chapter 4, we develop a multi-region Cournot-based electricity market model with non-linear inverse demand functions to find the impact of closing a base-load coal power plant on electricity prices in Australia's National Electricity Market. Calibrating the model with real price and demand data and building wind power availability scenarios based on the historical daily wind data, we run the market model 365 times and calculate the price volatility in NEM before and after closing down the coal power plant.

In Chapter 5, a bi-level optimization model is proposed to find the optimal storage capacity at each node to limit the price volatility in the market to a target level. In the upper level problem, the total storage capacity required to manage the price volatility is minimized, and in the lower level problem, the interaction between strategic/regulated generation, storage and transmission players is modeled using a stochastic (Bayesian) Cournot-based game with exponential inverse demand functions.

In Chapter 6, a bi-level optimization model is proposed to allocate a fixed amount of budget on wind and storage capacities to minimize the weighted sum of average price and price volatility in the market. In the upper level problem, the weighted sum of price and volatility is minimized by investing on battery and wind, and in the lower level problem, the non-cooperative interaction between all market players is modeled using a stochastic (Bayesian) Cournot-based game with exponential inverse demand functions.

Chapter 4

Impact of a Coal Power Plant Closure on a Multi-region Wholesale Electricity Market

Closure of a base-load power plant, based on either its aging state, or a national greenhouse reduction scheme, or transition to smart grids, may have a significant impact on wholesale electricity markets. This chapter presents a Cournot-based multi-region game model based on nonlinear inverse demand functions to formally analyze the impacts of a base-load plant closure on the price level and volatility (increase), and CO_2 *emission (decrease). Using the Hazelwood coal plant closure in Victoria, a state of Australia's National Electricity Market (NEM), as a case study, the simulation results indicate around 30% and 49% price and volatility increase in the wholesale market, and 210 million AU$ (+3.5%) higher annual power bills in Victoria for final consumers. However, being the most stable and least volatile region in NEM, Victoria mostly supports its neighboring regions in terms of price and volatility reduction even after the Hazelwood closure.*

4.1 Introduction

IN THIS chapter, a game-theoretic multi-region electricity market model based on nonlinear inverse demand functions is proposed. The model is used to analyze the regional electricity prices after closure of a base-load coal-fueled generator in an electricity market.

The contributions of this chapter are summarized as follows:

- A Mixed Complementarity Problem (MCP) is proposed to find the Nash Equilibrium solution of a Cournot-based multi-region electricity market model with nonlinear inverse demand functions, including strategic generators (with market power) and regulated transmission lines.

- We model the transmission lines as individual market participants likewise the other players in the game and solve the model as an MCP problem, which is computationally far more convenient than computing the electricity transmissions as a constraint for market clearing engines in Equilibrium Problem with Equilibrium Constraints (EPEC) electricity market models.

- The model is applied to the 5-node NEM market, as a case study, with realistic data from year 2015. Our numerical results explain the actual real-life market data events, e.g. price and demand, taking into account the market power of generation firms. The simulation covers 365 days in a year and is calibrated with the real wind generation and demand fluctuations.

- Lastly, the CO_2 emission of gas and coal-fueled power plants, which is affected by the electricity market price, is compared before and after the Hazelwood closure.

Under the proposed framework, we analyzed the impact of closing the Hazelwood plant in Victoria on the regional electricity prices in NEM. The price level and price volatility in different regions of NEM, the total profit the strategic generators make, and the total CO_2 emission are compared before and after the closure in our simulations. This kind of study can inform the market players and system operator of the consequences and ramifications of their decisions in advance.

The rest of this chapter is organized as follows. Section 4.2 illustrates the formulation of the system model and the proposed MCP problem. Section 4.3 presents the simulation results, and section 4.4 discusses the conclusion remarks.

4.2 System Model

We consider an electricity market consisting of I regions. Our market model includes synchronous generators, wind firms, and transmission interconnectors. Let $\mathcal{N}_i^{sg}$ be the set of synchronous generators, such as coal, gas, and hydro power plants, installed in region i, $\mathcal{N}_i^{\text{ig}}$ be the set of wind firms installed in region i, and $\mathcal{N}_i$ be the set of neighboring regions of region i connected with interconnectors. We determine the quantities of electricity generation and transmission and regional prices by solving a Cournot-based game between all market participants, that is, synchronous generators, wind firms, and transmission interconnectors, which are introduced in detail in Section 4.2.2.

In this chapter, we propose an MCP problem to solve a Cournot-based game-theoretical electricity market model with exponential inverse demand functions. This model differs from earlier ones, as it models a multi-region electricity market considering nonlinear inverse demand functions and considering generation and transmission players in a singe level. We use the model to analyze the impact of closing the existing coal power plants on the wholesale electricity market prices.

4.2.1 Wholesale Price Function

The market price in region i at time t is modeled by an exponential function:

$$P_{it}\left(\boldsymbol{q_{it}}\right) = \alpha_{it} e^{-\beta_{it}\left(\sum\limits_{m\in\mathcal{N}_i^{\text{ig}}} q_{mit}^{\text{ig}} + \sum\limits_{n\in\mathcal{N}_i^{\text{sg}}} q_{nit}^{\text{sg}} + \sum\limits_{j\in\mathcal{N}_i^{\text{tr}}} q_{ijt}^{\text{tr}}\right)} \tag{4.1}$$

where the coefficients α_{it}, β_{it} are positive real values in the inverse demand function, q_{mit}^{ig} is the generation quantity of the mth wind generator installed in region i at time t, q_{nit}^{sg} is the generation quantity of the nth synchronous generator installed in region i at time t, and q_{ijt}^{tr} is the transmitted quantity from region j to region i at time t via its interconnector. The collection of strategies of all firms located in region i at time t is denoted by $\boldsymbol{q_{it}}$. Section 3.2 explains why we use an exponential inverse demand function instead of a linear one.

4.2.2 Market Participants

In our game model, the market players consist of synchronous generators and wind firms deciding on their electricity generation, and transmission lines deciding on their electricity exchange. In order to find its best response function, each market participant decides on its decision variables, considering other players' decision variables as an input, maximizing its objective function subject to the constraints corresponding to the technical and operational limitations. The intersection of the best responses of all players is defined as the Nash Equilibrium (NE) and solution of the game.

In our formulation, the wind firms and the synchronous generators are assumed to be strategic, but the transmission firms are modeled as either strategic or regulated players.

Definition 4.1. *A strategic (price maker) firm decides on its strategies over the operation horizon* $\{1, ..., N_{\mathrm{T}}\}$ *maximizing its aggregate profit over the operation horizon. On the other hand, a regulated (price taker) firm aims to maximize the net market value, i.e. the social welfare [77].*

Wind Generators

The best response of the mth wind (intermittent) generator in region i is obtained by solving the following optimization problem:

$$\max_{\left\{q^{\mathrm{ig}}_{mit}\right\}_t \succeq 0} \sum_{t=1}^{N_{\mathrm{T}}} P_{it}\left(\boldsymbol{q_{it}}\right) q^{\mathrm{ig}}_{mit} \tag{4.2a}$$

s.t.

$$q^{\mathrm{ig}}_{mit} \leq \omega_{it} Q^{\mathrm{ig}}_{mi} \quad \forall t \tag{4.2b}$$

$$P_{it}\left(\boldsymbol{q_{it}}\right) \leq P^{\mathrm{cap}} \quad \forall t \tag{4.2c}$$

where q^{ig}_{mit} is the generation level of the mth wind generator installed in region i at time t, Q^{ig}_{mi} is the capacity of the wind generator mi, ω_{it} is the normalized wind power availability coefficient of region i at time t, which represents the regional wind power availability fluctuations, and P^{cap} represents the price cap in the market, which is, for example, 11000 \$/MWh in Australian NEM. The constraint (4.2b) considers the wind energy availability effect on power generation of the individual wind firm mi, and the constraint (4.2c) secures the price cap in the market.

Synchronous Generators

The best response of the nth synchronous generator installed in region i is determined by solving the following optimization problem:

$$\max_{\left\{q^{\mathrm{sg}}_{nit}\right\}_t \succeq 0} \sum_{t=1}^{N_{\mathrm{T}}} \left(P_{it}\left(\boldsymbol{q_{it}}\right) - c^{\mathrm{sg}}_{ni}\right) q^{\mathrm{sg}}_{nit} \tag{4.3a}$$

s.t.

$$q^{\mathrm{sg}}_{nit} \leq Q^{\mathrm{sg}}_{ni} \quad \forall t \tag{4.3b}$$

$$q^{\mathrm{sg}}_{nit} - q^{\mathrm{sg}}_{ni(t-1)} \leq R^{\mathrm{up}}_{ni} \quad \forall t \tag{4.3c}$$

$$q^{\mathrm{sg}}_{ni(t-1)} - q^{\mathrm{sg}}_{nit} \leq R^{\mathrm{dn}}_{ni} \quad \forall t \tag{4.3d}$$

$$P_{it}\left(\boldsymbol{q_{it}}\right) \leq P^{\mathrm{cap}} \quad \forall t \tag{4.3e}$$

where q^{sg}_{nit} is the generation level of the nth synchronous generator installed in region i at time t, Q^{sg}_{ni} is the generation capacity of the synchronous generator ni, and c^{sg}_{ni} is its marginal cost of generation. The constraint (4.3b) considers the generation capacity of the synchronous generator ni, the constraints (4.3c) and (4.3d) ensure that the ramping limitations of the synchronous generator ni are always met, and the constraint (4.3e) secures the price cap in the market.

Transmission Firms

The best response of the transmission firm connecting the regions i and j is determined by solving the following optimization problem:

$$\max_{\left\{q^{\mathrm{tr}}_{jit}, q^{\mathrm{tr}}_{ijt}\right\}_t} \sum_{t=1}^{N_{\mathrm{T}}} \left(1 - \gamma^{\mathrm{tr}}_{ij}\right) \left(P_{jt}\left(\boldsymbol{q_{jt}}\right) q^{\mathrm{tr}}_{jit} + P_{it}\left(\boldsymbol{q_{it}}\right) q^{\mathrm{tr}}_{ijt}\right) + \gamma^{\mathrm{tr}}_{ij} \left(\frac{P_{jtw}\left(\boldsymbol{q_{jt}}\right)}{-\beta_{jt}} + \frac{P_{itw}\left(\boldsymbol{q_{it}}\right)}{-\beta_{it}}\right) \tag{4.4a}$$

s.t.

$$q^{\mathrm{tr}}_{ijt} = -q^{\mathrm{tr}}_{jit} \quad \forall t \tag{4.4b}$$

$$-Q^{\mathrm{tr}}_{ij} \leq q^{\mathrm{tr}}_{ijt} \leq Q^{\mathrm{tr}}_{ij} \quad \forall t \tag{4.4c}$$

$$P_{kt}\left(\boldsymbol{q_{kt}}\right) \leq P^{\text{cap}} \quad k \in \{i,j\}, \quad \forall t \tag{4.4d}$$

where q^{tr}_{ijt} is the electricity exchange from region j to region i at time t, and Q^{tr}_{ij} is the capacity of the transmission line ij. The constraint (4.4b) ensures that the transmission levels calculated on both directions of a line are identical, the constraint (4.4c) considers the transmission capacity of the line ij, and the constraint (4.4d) secures the price cap in the market. Note that the term $P_{jt}\left(\boldsymbol{q_{jt}}\right) q^{\text{tr}}_{jit} + P_{it}\left(\boldsymbol{q_{it}}\right) q^{\text{tr}}_{ijt}$ is equal to $\left(P_{it}\left(\boldsymbol{q_{it}}\right) - P_{jt}\left(\boldsymbol{q_{jt}}\right)\right) q^{\text{tr}}_{ijt}$ which implies that the transmission firm may make profit by trading the electricity from the node with lower price to the higher price node, and derivative of term $\frac{P_{jtw}\left(\boldsymbol{q_{jt}}\right)}{-\beta_{jt}} + \frac{P_{itw}\left(\boldsymbol{q_{it}}\right)}{-\beta_{it}}$ with respect to q^{tr}_{ijt}, given $q^{\text{tr}}_{ijt} = -q^{\text{tr}}_{jit}$, is $P_{it}\left(\boldsymbol{q_{it}}\right) - P_{jt}\left(\boldsymbol{q_{jt}}\right)$ which implies the firm may trade electricity without market power. Therefore, when the coefficient γ^{tr}_{ij} is zero, the transmission firm ij is modeled as a strategic player (profit maximizer), and when the coefficient γ^{tr}_{ij} is one, the firm is modeled as a regulated player (social welfare maximizer).

Transmission firms or interconnectors are usually controlled by the market operator. They are regulated to maximize the social welfare in the market. The existing literature discusses the markets with regulated transmission firms as electricity markets with transmission constraint, e.g., see [7]. However, there are unregulated transmission firms in some electricity markets, who make revenue by trading electricity across the regions [78].

4.2.3 Solution Approach

Here, we seek for the intersection of the best response functions of all players in our problem, i.e. the solution to the Karush-Kuhn-Tucker (KKT) conditions of all players. The intersection of the best response functions of all players represents the NE solution. The existence of a NE point in our problem is stated in Proposition 4.1.

Proposition 4.1. *As the objective function of each player in our model is continuous and quasi-concave in its strategy and their strategy space is compact, convex, and non-empty, our game model admits a Nash Equilibrium solution.*

Proof: The proof follows from Theorem 1.2 in [79].

Therefore, we look for a solution that satisfies the KKT conditions of wind generators, (4.2a-4.2c), synchronous generators, (4.3a-4.3e), and transmission lines, (4.4a-4.4d). Note that deriving the KKT conditions of the players' optimization problems are discussed in detail in [52]. The resulting MCP problem is as follows:

$$
\begin{aligned}
&\mathrm{KKT}\,(4.2a - 4.2c)\,, \mathrm{KKT}\,(4.3a - 4.3e)\,, \mathrm{KKT}\,(4.4a - 4.4d)\,:\\
&m \in \{1, ..., N_i^{\mathrm{ig}}\}, n \in \{1, ..., N_i^{\mathrm{sg}}\}, i, j \in \{1, ..., I\}\\
&t \in \{1, ..., N_{\mathrm{T}}\}
\end{aligned}
$$

where the decision variables are the bidding strategies of all firms, and the set of Lagrange multipliers in KKT conditions. The problem is solved by PATH solver in GAMS software.

4.3 Case Study and Simulation Results

In this section, we study the impact of closing a coal power plant on wholesale electricity prices in market NEM.

4.3.1 Model Calibration

We simulated the NEM using a Cournot-based wholesale electricity market model with exponential inverse demand functions. The coefficients of the inverse demand function are calibrated with the real data of price and demand in five regions of NEM in 2015. In order to verify the accuracy of our model in real market simulation, we compared our simulation results for an average day splitted into 24 hours with the real historical average price and demand data. The price and demand levels are calculated with the error terms of 6.4% and 4.7% respectively. Then, we update the coefficients α and β in the inverse demand functions for each day in all seasons, 365 days, based on the difference of the historical price and demand at each day (scenario) from the average levels.

4.3.2 Model Simulation for 365 Days

The stochastic parameters, such as intermittent power generation and demand variation, are usually modeled by a set of scenarios in scenario-based electricity market models [32, 33]. Scenario reduction techniques are applied to select any set of scenarios [80].

Instead of incorporating the scenario reduction simplifications, we capture the intermittency and the price volatility existing in the market by repeating our simulations for all 365 days in our model.

In order to observe the price fluctuations in different days during a year, we repeated our simulation for all 365 days (24 hours) in year 2015, and captured the intermittencies of wind power availability and demand variation in the model. Fig. 4.1 illustrates the hourly variations of demand and wind power availability in 2015. The coefficients α_{it} and β_{it} in the inverse demand function are calibrated with the historical price and demand data enabling the model to follow the expected price and demand variations. The normalized wind power availability coefficient w_{it} is also calibrated based on the historical hourly wind power generation in five regions of NEM during the year 2015.

We conducted our study to find the impact of closing the Hazelwood coal power plant (1600 MW) in VIC on the electricity prices in different NEM's regions. Table 4.1 indicates the regional average prices in NEM before and after the Hazelwood closure. Our simulation results show that the average price of electricity goes up about 30.13% in VIC and about 6.87% in total NEM after closing the plant Hazelwood, which shows more price increase in the region in which closure happens. The electricity prices in QLD, the region that is not directly connected to the region VIC, are almost unchanged after the closure. Note that given the transmission and distribution cost of 120 $/MWh, the final consumer prices in VIC goes up about 6.5% compared to the announced amount of 4% in news (www.abc.net.au).

The electricity transmission direction between interconnected regions, to some extent, indicates how a coal plant closure in one region affects the electricity prices in other regions. As the region TAS behaves as a net importer of electricity from VIC before the closure, the Hazelwood closure in VIC increases the prices in TAS notably. The region SA is also a net importer of electricity from VIC, but the Hazelwood closure does not

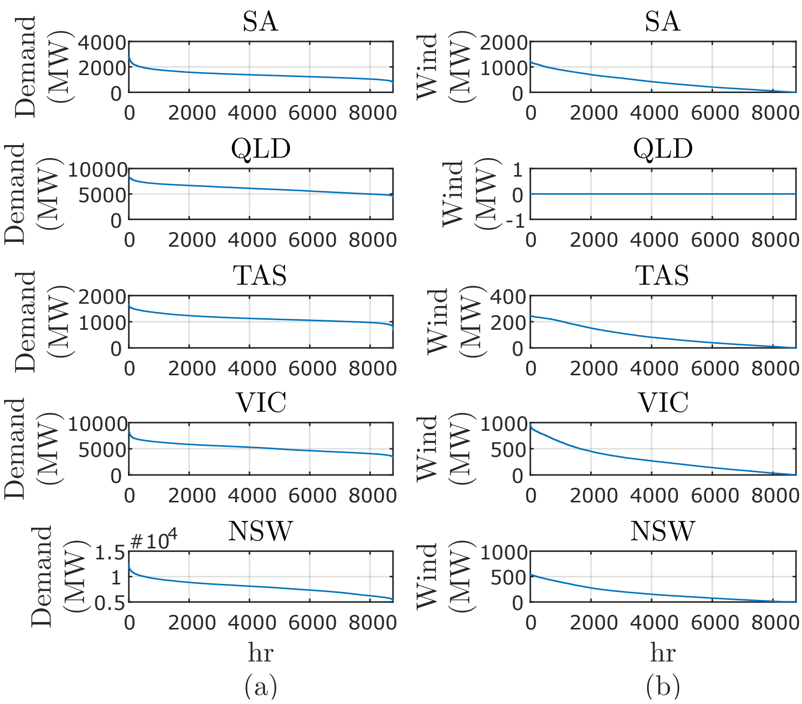

Figure 4.1: Sorted historical data of hourly (a) electricity demand and (b) wind power availability in five regions of NEM during the year 2015.

increase the average price in SA significantly due to the congestion of the interconnector between SA and VIC.

Table 4.1: Wholesale electricity prices \$/MWh in five-node NEM market, considering the closure of coal power plant Hazelwood in VIC.

Price (\$/MWh)	SA	QLD	TAS	**VIC**	NSW	NEM
Before closure	73.10	72.14	49.59	**34.18**	39.87	48.80
After closure (change%)	75.06 (2.67%)	72.16 (0.02%)	53.80 (8.50%)	**44.48 (30.12%)**	40.21 (0.86%)	52.16 (6.87%)

The closure of Hazelwood power plant has different effects on electricity prices in different regions at different times. Fig. 4.2 indicates the probability distribution of hourly electricity prices in the region VIC and in the total NEM. The probability distributions of hourly prices in VIC and the total NEM indicate rightward shifts after the Hazelwood closure. The price increment, i.e. rightward shift of the price probability distribution, is more notable in VIC compared to the total NEM. The rate of average price increment in

VIC is almost five times of the rate in total NEM.

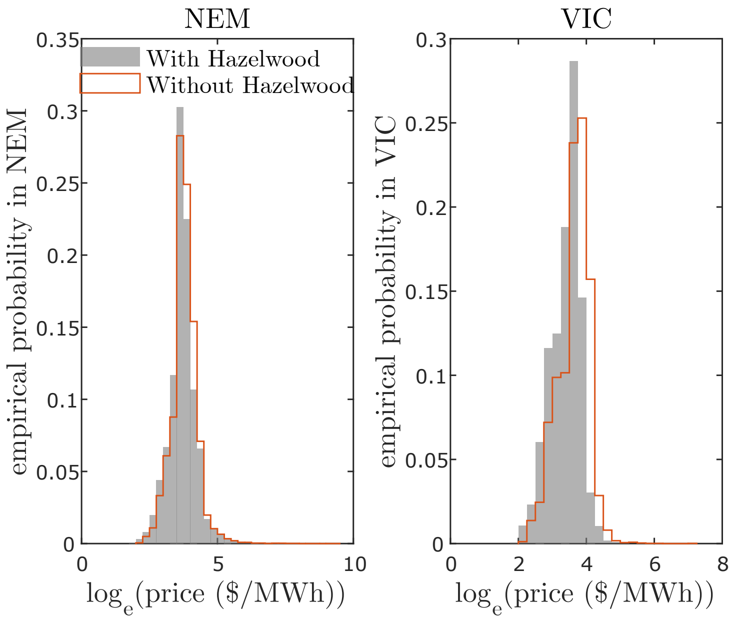

Figure 4.2: Probability distribution of hourly prices in NEM and VIC, considering the closure of coal power plant Hazelwood in VIC.

The effect of closing the Hazelwood coal power plant on daily peak prices is also investigated in our work. Fig. 4.3 illustrates the probability distributions of daily peak prices in the region VIC and the total NEM. Our simulation results show that the daily peak prices in the region VIC go up significantly after closing the plant Hazelwood. The daily peak price of 1213 $/MWh is calculated in VIC after the closure, which is almost twice as high as the pre-closure record of 618 $/MWh. However, the very high prices close to the cap price of 11000 $/MWh mostly occur in the regions QLD and SA, before and after the closure. Therefore, the Hazelwood closure although quite often increases the daily peak prices in NEM, it does not increase the probability of the very high prices close to the cap price in the market.

The increase of the market price is related to reduction of generation because of the Hazelwood closure and to increase of the remaining generators' market power in the market. In spite of less electricity generation, the generation companies make more profit after the Hazelwood closure. Table 4.2 compares the regional electricity generation profits before and after the Hazelwood closure in NEM. Surprisingly, not only do the remaining

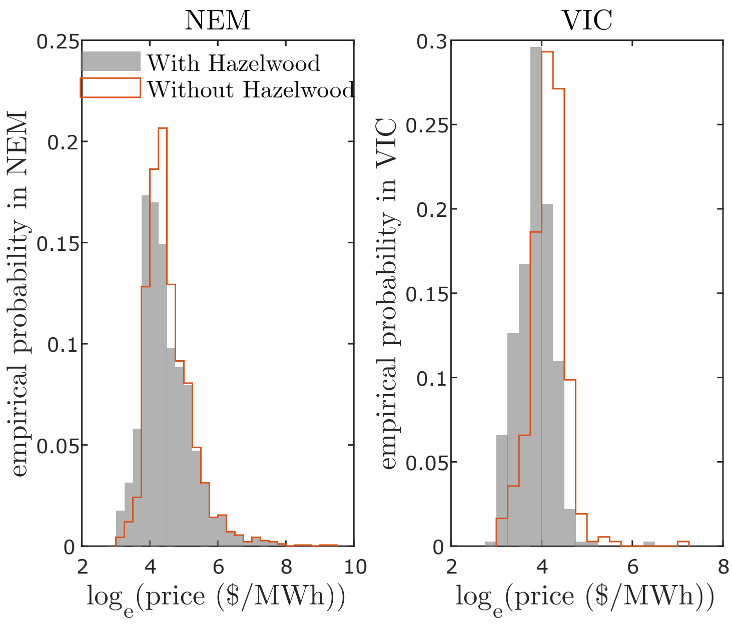

Figure 4.3: Probability distribution of daily peak prices in NEM and VIC, considering the closure of coal power plant Hazelwood in VIC.

generation companies make higher profits compared to their pre-closure profits, , but also the total amount of generation profit, including the Hazelwood's profit, is also higher after the closure, as a result of market power increase after the Hazelwood closure.

Table 4.2: The annual electricity generation profit (billion$ per year) in five-node NEM market, considering the closure of coal power plant Hazelwood in VIC.

Profit (b$/year)	SA	QLD	TAS	**VIC**	NSW	NEM
Before closure	0.38	1.55	0.32	**1.33**	1.08	4.68
After closure (change%)	0.38 (+2.2%)	1.55 (+0.0%)	0.36 (+9.9%)	**1.54 (+15.9%)**	1.11 (+2.9%)	4.96 (+6.1%)

The standard deviation of electricity prices, consistent with $\sqrt{\frac{\sum_{t=1}^{N_\mathrm{T}}(P_{it}-\bar{P}_i)^2}{N_\mathrm{T}}}$ where $\bar{P}_i$ is the average price in region i, measures the price volatility and roughly indicates in which regions very high electricity prices happen. Table 4.3 indicates the standard deviation of electricity prices in different regions of the NEM. The state VIC although faces the price volatility increment of 49% after the closure, it holds relatively low levels of price standard deviation in the market NEM before and after the closure, which shows that VIC is the most stable and least volatile region in NEM. In fact, before and after the closure, VIC mostly supports the other regions in terms of reducing their price level and price volatility by exporting electricity via its interconnectors. It is observed that closing off a power plant in VIC does not result in the unfavored very high prices close to the cap price in NEM.

Table 4.3: Standard deviation of wholesale electricity prices $/MWh in five-node NEM market, considering the closure of coal power plant Hazelwood in VIC.

Deviation ($/MWh)	SA	QLD	TAS	**VIC**	NSW	NEM
Before closure	85.67	196.62	16.30	**15.15**	30.06	97.36
After closure (change%)	85.57 (-0.1%)	196.49 (-0.07%)	16.70 (+2.4%)	**22.62 (+49.2%)**	29.90 (-0.5%)	97.59 (+0.2%)

Lastly, closure of the Hazelwood coal power plant in VIC changes the greenhouse gas emission of CO_2 from combustion of each fuel type, e.g. gas and coal, in the market NEM. Table 4.4 compares the levels and changes of CO_2 emission in NEM before and after the closure of the plant Hazelwood. After the closure, the CO_2 emission in NEM reduces from coal combustion and increases from gas combustion. The decrease of coal-fueled electricity generation after the plant closure results in higher electricity prices, and consequently the more expensive gas-fueled electricity generation in the market becomes more incentivized. In total, assuming the emission factor of 0.93 ($tonne_{CO_2}$/MWh) for coal and 0.55 ($tonne_{CO_2}$/MWh) for gas, the aggregated CO_2 emission in NEM from coal and gas combustion decreases about 5.8% per year after closing the Hazelwood power plant.

Table 4.4: Greenhouse gas emission of CO_2 (million tonne per year) in coal and gas-fueled power plants in NEM, considering the closure of coal power plant Hazelwood in VIC.

Emission (mtonne/year)	Coal	Gas	Total
Before closure	127	8.94	136
After closure (change %)	118 (-7.0%)	10.0 (+11.8%)	128 (-5.8%)

4.4 Conclusion

Closing down the base-load coal power plants, due to aging or intensive greenhouse gas emission or growth of smart grids, is gradually taking place in many countries over the world. Our study presents an MCP problem which solves a multi-region electricity market game between wind firms, synchronous generators, and transmission lines before and after closing a coal power plant in the market. Based on our numerical results, the impact of closing the Hazelwood coal power plant in VIC on the electricity market NEM can be summarized as:

- In a multi-region electricity market, coal power plant closure in one region may affect the electricity prices in different regions. Closing the Hazelwood plant in VIC has the highest impact on electricity prices in the region VIC and then on its neighboring regions TAS and SA.
- The interconnectors also determine how a coal power plant closure may affect the electricity prices in its neighboring regions. Both regions of SA and TAS are net importers of electricity from VIC, but the price in SA does not change significantly after the coal plant closure in VIC. The fact that the interconnector between SA and VIC is usually congested prevents observing immense price changes in SA after the Hazelwood closure.
- The region VIC faces a bounded price volatility increment inside its own region after the Hazelwood closure. However, VIC, as the most stable and least volatile region in NEM, continues to support its neighboring regions in terms of price level and price volatility reduction even after the closure.
- The electricity generation companies enjoy higher amount of market power after the Hazelwood closure, especially in VIC. Due to decrease of power generation capacity in the market after the closure, generation companies may strategically keep the prices higher and earn more profits.
- Although the closure of the Hazelwood coal plant increases the electricity prices in NEM and incentivizes more gas fueled power generation and consequently leads

to more emission from the gas generators, the aggregate effect of closing the Hazelwood plant down results in about 5.8% less CO_2 emission from the coal and gas-powered generators after the Hazelwood closure.

We observed in this chapter that closure of a coal power plant may increase the market price and its volatility significantly. In Chapter 5, we study the integration of storage in the network to find how it can help to reduce the high levels of electricity prices and price volatility in the market.

Chapter 5

Impact of Optimal Storage Allocation on Price Volatility in Electricity Markets

Recent studies show that the fast growing expansion of wind power generation may lead to extremely high levels of price volatility in wholesale electricity markets. Storage technologies, regardless of their specific forms, e.g. pump-storage hydro, large-scale or distributed batteries, are capable of alleviating the extreme price volatility levels due to their energy usage time shifting, fast-ramping and price arbitrage capabilities. In this chapter, we propose a stochastic bi-level optimization model to find the optimal nodal storage capacities required to achieve a certain price volatility level in a highly volatile energy-only electricity market. The decision on storage capacities is made in the upper level problem and the operation of strategic/regulated generation, storage and transmission players is modeled in the lower level problem using an extended stochastic (Bayesian) Cournot-based game. The South Australia (SA) electricity market, which has recently experienced high levels of price volatility, and a 30-bus IEEE system are considered as the case studies. Our numerical results indicate that 50% price volatility reduction in SA electricity market can be achieved by installing either 430 MWh regulated storage or 530 MWh strategic storage. In other words, regulated storage firms are more efficient in reducing the price volatility than strategic storage firms.

5.1 Introduction

IN THIS chapter, a stochastic optimization framework is proposed for finding the required nodal storage capacities in electricity markets with high levels of wind penetration such that the price volatility in the market is kept below a certain level. Using a proper storage allocation framework, the policy makers and market/system operators can compute the required nodal storage capacities for managing the price volatility level in electricity markets. Although the current cost of storage systems is relatively high, the support from governments (in the form of subsidies) and the eventual decline of the technology cost can lead to large scale integration of storage systems in electricity markets.

The contributions of this chapter are summarized as follows:

- A bi-level optimization model is proposed to find the optimal nodal storage capacities required for avoiding the extreme price volatility levels in a nodal electricity market.
- In the upper level problem, the total storage capacity is minimized subject to a price volatility target constraint in each node and at each time.
- In the lower level problem, the non-cooperative interaction between generation, transmission and storage players in the market is modeled as a stochastic (Bayesian) Cournot-based game with an exponential inverse demand function. Note that the equilibrium prices at the lower level problem are functions of the storage capacities. The operation of storage devices at the lower level problem is modeled without introducing binary variables.
- The existence of Bayesian Nash Equilibrium (Bayes-NE) [81] under the exponential inverse demand function is established for the lower level problem.

Under the proposed framework, the size of storage devices at two nodes of South Australia (SA) and Victoria (VIC) in NEM and also the size of storage in a 30-bus IEEE system is determined such that the market price volatility is kept below a desired level at all times. The desired level of price volatility can be determined based on various criteria such as net revenue earned by the market players, occurrence frequency of undesirable prices, number of CPT breaches, etc [82].

The rest of this chapter is organized as follows. The system model and the proposed bi-level optimization problem are formulated in Section 5.2. The equilibrium analysis of the lower level problem and the solution method are presented in Section 5.3. The simulation results are presented in Section 5.4. The conclusion remarks are discussed in Section 5.5.

5.2 System Model

Similar to the market model in Chapter 5, consider a nodal electricity market with I nodes. Storage players are also included in our market model in this chapter. Let $\mathcal{N}_i^{\mathrm{sg}}$ be the set of synchronous generators, such as coal and gas power plants, located in node i and $\mathcal{N}_i^{\mathrm{ig}}$ be the set of wind generation firms located in node i. The set of neighboring nodes of node i is denoted by $\mathcal{N}_i$. Since the wind availability is a stochastic parameter, a scenario-based model, with N_{w} different scenarios, is considered to model the wind availability in the electricity network. The nodal prices in our model are determined by solving a stochastic (Bayesian) Cournot-based game among all market participants, that is, synchronous generators, wind firms, storage firms and transmission interconnectors which are introduced in detail in the lower level problem, given the wind power availability scenarios. The decision variables, feasible region, and objective function for each player in our game model are discussed in Section 5.2.2. In a Cournot game, each producer (generator) competes for maximizing its profit which is defined as its revenue minus its production cost, given the generation of other players. The revenue of each player is its production level times the market price. Also, the market price is a function of total generation. Following the standard Cournot game models, any player in our model maximizes its objective function given the decision variables of other players (generation, transmission, and storage firms). Considering different wind power availability scenarios with given probabilities makes our game model consistent with the Bayesian game definition. In a Bayesian game, players maximize their expected utility over a set of scenarios with a given probability distribution [81].

In this chapter, we present a bi-level optimization approach for finding the minimum required total storage capacity in the market such that the market price volatility stays within a desired limit at each time.

5.2.1 Upper-level Problem

In the upper-level optimization problem, we determine the nodal storage capacities such that a price volatility constraint is satisfied in each node at each time. In this chapter, estimates of variances are used to capture the volatilities [83], i.e., the variance of market price is considered as a measure of price volatility. The variance of the market price in node i at time t, i.e., $\mathrm{Var}\big(P_{itw}\big)$, can be written as:

$$\begin{aligned}\mathrm{Var}\left(P_{itw}\right) &= \mathsf{E}_w\left[\left(P_{itw}\left(\boldsymbol{q}_{itw}\right)\right)^2\right] - \left(\mathsf{E}_w\left[P\left(\boldsymbol{q}_{itw}\right)\right]\right)^2 \\ &= \sum_w \left(P_{itw}\left(\boldsymbol{q}_{itw}\right)\right)^2 \Psi_w - \left(\sum_w P_{itw}\left(\boldsymbol{q}_{itw}\right)\Psi_w\right)^2 \end{aligned} \tag{5.1}$$

where Ψ_w is the probability of scenario w, and $P_{itw}\left(\boldsymbol{q}_{itw}\right)$ is the market price in node i at time t under the wind availability scenario w, which is a function of the collection of all players' strategies $\boldsymbol{q}_{itw}$, i.e., the decision variables in the lower level game.

The notion of variance quantifies the *effective* variation range of random variables, i.e. a random variable with a small variance has a smaller effective range of variation when compared with a random variable with a large variance.

Given the price volatility relation (5.1) based on the Bayes-NE strategy collection of all firms $\boldsymbol{q}^{\star}_{itw}$, the upper-level optimization problem is given by:

$$\min_{\left\{Q^{\mathrm{st}}_i\right\}_i} \sum_{i=1}^{I} Q^{\mathrm{st}}_i$$

s.t.

$$Q^{\mathrm{st}}_i \geq 0 \quad \forall i \tag{5.2a}$$

$$\mathrm{Var}\left(P_{itw}\left(\boldsymbol{q}^{\star}_{itw}\right)\right) \leq \sigma_0^2 \quad \forall i, t \tag{5.2b}$$

where Q^{st}_i is the storage capacity in node i, $P_{itw}\left(\boldsymbol{q}^{\star}_{itw}\right)$ is the market price in node i at time t under the wind availability scenario w, and σ_0^2 is the price volatility target. The price volatility of the market is defined as the maximum variance of market price, *i.e.* $\max_{it} \mathrm{Var}(P_{itw}(\boldsymbol{q}^{\star}_{itw}))$.

5.2.2 Lower-level Problem

In the lower-level problem, the nodal market prices and the Bayes-NE strategies of firms are obtained by solving an extended stochastic Cournot-based game between wind generators, storage firms, transmission firms, and synchronous generators. Our model differs from a standard Cournot game, such that it includes regulated players in addition to strategic players in generation, storage and transmission levels.

Definition 5.1. *A strategic (price maker) firm decides on its strategies over the operation horizon* $\{1, ..., N_{\mathrm{T}}\}$ *such that its aggregate expected profit, over the operation horizon, is maximized. On the other hand, a regulated (price taker) firm aims to maximize the net market value, i.e. the social welfare [77].*

The market price in node i at time t under the wind availability scenario w is given by an exponential inverse demand function (Section 3.2):

$$P_{itw}\left(\boldsymbol{q}_{itw}\right) = \alpha_{it} e^{-\beta_{it}\left(q^{\mathrm{st}}_{itw} + \sum\limits_{m\in\mathcal{N}_i^{\mathrm{ig}}} q^{\mathrm{ig}}_{mitw} + \sum\limits_{n\in\mathcal{N}_i^{\mathrm{sg}}} q^{\mathrm{sg}}_{nitw} + \sum\limits_{j\in\mathcal{N}_i} q^{\mathrm{tr}}_{ijtw}\right)} \tag{5.3}$$

where α_{it}, β_{it} are positive real values in the inverse demand function, q^{sg}_{nitw} is the generation strategy of the nth synchronous generator located in node i at time t under scenario w, q^{ig}_{mitw} is the generation strategy of the mth wind generator located in node i at time t under scenario w, q^{st}_{itw} is the charge/discharge strategy of the storage firm in node i at time t under scenario w, q^{tr}_{ijtw} is the strategy of transmission firm located between node i and node j at time t under scenario w. The collection of strategies of all firms located in node i at time t under the scenario w is denoted by $\boldsymbol{q}_{itw}$. Note that the total amount of power supply from the generation and storage firms plus the net import/export, i.e., $q^{\mathrm{st}}_{itw} + \sum\limits_{m\in\mathcal{N}_i^{\mathrm{ig}}} q^{\mathrm{ig}}_{mitw} + \sum\limits_{n\in\mathcal{N}_i^{\mathrm{sg}}} q^{\mathrm{sg}}_{nitw} + \sum\limits_{j\in\mathcal{N}_i} q^{\mathrm{tr}}_{ijtw}$, is equal to the net electricity demand in each node, at each time and under each scenario, which represents the nodal electricity balance in our model.

In what follows, the variable μ is used to indicate the associated Lagrange variable with its corresponding constraint in the model.

Wind Generators

The Bayes-NE strategy of the mth wind (intermittent) generator in node i is obtained by solving the following optimization problem:

$$\max_{\left\{q^{\text{ig}}_{mitw}\right\}_{tw} \succeq 0} \sum_{w} \Psi_w \sum_{t=1}^{N_{\text{T}}} P_{itw}\left(\boldsymbol{q}_{itw}\right) q^{\text{ig}}_{mitw} \left(1-\gamma^{\text{ig}}_{mi}\right) + \gamma^{\text{ig}}_{mi} \left(\frac{P_{itw}\left(\boldsymbol{q}_{itw}\right)}{-\beta_{it}}\right)$$

s.t.

$$q^{\text{ig}}_{mitw} \leq Q^{\text{ig}}_{mitw} \quad : \quad \mu^{\text{ig,max}}_{mitw} \quad \forall t, w \tag{5.4a}$$

$$P_{itw}\left(\boldsymbol{q}_{itw}\right) \leq P^{\text{cap}} \quad : \quad \mu^{\text{ig,cap}}_{mitw} \quad \forall t, w \tag{5.4b}$$

where q^{ig}_{mitw} and Q^{ig}_{mitw} are the generation level and the available wind capacity of the mth wind generator located in node i at time t under scenario w. The parameter P^{cap} represents the price cap in the market, which is, for instance, 11000 \$/MWh in the NEM market. Setting cap price in electricity markets also aims to limit the price levels and price volatility levels. Note that the wind availability changes in time in a stochastic manner, and the wind firm's bids depend on the wind availability. As a result, the nodal prices and decisions of the other firms become stochastic in our model [33].

The mth wind firm in node i acts as a strategic firm in the market if γ^{ig}_{mi} is equal to zero and acts as a regulated firm if γ^{ig}_{mi} is equal to one. The difference between regulated and strategic players corresponds to the strategic price impacting capability. In fact, a regulated firm behaves as a price taker player while a strategic firm behaves as a price maker player.

Storage Firms

Storage firms benefit from price difference at different times to make profit, i.e. they sell the off-peak stored electricity at higher prices at peak times. The Bayes-NE strategy of storage firm located in node i is determined by solving the following optimization problem:

$$\max_{\substack{\left\{q_{itw}^{\text{dis}},q_{itw}^{\text{ch}}\right\}_{tw}\succeq 0\\ ,\left\{q_{itw}^{\text{st}}\right\}_{tw}}} \sum_{w}\Psi_w \sum_{t=1}^{N_{\text{T}}} P_{itw}\left(\boldsymbol{q}_{itw}\right) q_{itw}^{\text{st}}\left(1-\gamma_i^{\text{st}}\right) - c_i^{\text{st}}\left(q_{itw}^{\text{dis}}+q_{itw}^{\text{ch}}\right) + \gamma_i^{\text{st}}\left(\frac{P_{itw}\left(\boldsymbol{q}_{itw}\right)}{-\beta_{it}}\right)$$

s.t.

$$q_{itw}^{\text{st}} = \eta_i^{\text{dis}} q_{itw}^{\text{dis}} - \frac{q_{itw}^{\text{ch}}}{\eta_i^{\text{ch}}} \quad : \quad \mu_{itw}^{\text{st}} \quad \forall t,w \tag{5.5a}$$

$$q_{itw}^{\text{dis}} \le \zeta_i^{\text{dis}} Q_i^{\text{st}} \quad : \quad \mu_{itw}^{\text{dis,max}} \quad \forall t,w \tag{5.5b}$$

$$q_{itw}^{\text{ch}} \le \zeta_i^{\text{ch}} Q_i^{\text{st}} \quad : \quad \mu_{itw}^{\text{ch,max}} \quad \forall t,w \tag{5.5c}$$

$$0 \le \sum_{t'=1}^{t}\left(q_{it'w}^{\text{ch}} - q_{it'w}^{\text{dis}}\right)\Delta \le Q_i^{\text{st}} : \mu_{itw}^{\text{st,min}}, \mu_{itw}^{\text{st,max}} \quad \forall t,w \tag{5.5d}$$

$$P_{itw}\left(\boldsymbol{q}_{itw}\right) \le P^{\text{cap}} \quad : \quad \mu_{itw}^{\text{st,cap}} \quad \forall t,w \tag{5.5e}$$

where q_{itw}^{dis} and q_{itw}^{ch} are the discharge and charge levels of the storage firm in node i at time t under scenario w, respectively, c_i^{st} is the unit operation cost, η_i^{ch} ,η_i^{dis} are the charging and discharging efficiencies, respectively, and q_{itw}^{st} is the net supply/demand of the storage firm in node i. The parameter ζ_i^{ch} (ζ_i^{dis}) is the percentage of storage capacity Q_i^{st}, which can be charged (discharged) during time period Δ. It is assumed that the storage devices are initially fully discharged. The energy level of the storage device in node i at each time is limited by its capacity Q_i^{st}. Note that the nodal market prices depend on the storage capacities, *i.e.* Q_i^{st}s, through the constraints (5.5b)-(5.5d). This dependency allows the market operator to meet the volatility constraint using the optimal values of the storage capacities. The storage capacity variables are the only variables that couple the scenarios in the lower level problem. Therefore, each scenario of the lower lever problem can be solved separately for any storage capacity amount. The storage firm in node i acts as a strategic firm in the market if γ_i^{st} is equal to zero and acts as a regulated firm if γ_i^{st} is equal to one.

Proposition 5.1. *At the Bayes-NE of the lower level game, each storage firm is either in the charge mode or discharge mode at each scenario, i.e. the charge and discharge levels of each storage firm cannot be simultaneously positive at the NE of each scenario.*

Proof: See Appendix A.

Synchronous Generators

Synchronous generators include coal, gas, hydro and nuclear power plants. The Bayes-NE strategy of nth synchronous generator located in node i is determined by solving the following optimization problem:

$$\max_{\left\{q^{\text{sg}}_{nitw}\right\}_{tw}\succeq 0} \sum_{w} \Psi_w \sum_{t=1}^{N_{\text{T}}} P_{itw}\left(\boldsymbol{q}_{itw}\right) q^{\text{sg}}_{nitw}\left(1-\gamma^{\text{sg}}_{ni}\right) - c^{\text{sg}}_{ni} q^{\text{sg}}_{nitw} + \gamma^{\text{sg}}_{ni}\left(\frac{P_{itw}\left(\boldsymbol{q}_{itw}\right)}{-\beta_{it}}\right)$$

s.t.

$$q^{\text{sg}}_{nitw} \leq Q^{\text{sg}}_{ni} \quad : \quad \mu^{\text{sg,max}}_{nitw} \quad \forall t, w \tag{5.6a}$$

$$q^{\text{sg}}_{nitw} - q^{\text{sg}}_{ni(t-1)w} \leq R^{\text{up}}_{ni} Q^{\text{sg}}_{ni} \quad : \quad \mu^{\text{sg,up}}_{nitw} \quad \forall t, w \tag{5.6b}$$

$$q^{\text{sg}}_{ni(t-1)w} - q^{\text{sg}}_{nitw} \leq R^{\text{dn}}_{ni} Q^{\text{sg}}_{ni} \quad : \quad \mu^{\text{sg,dn}}_{nitw} \quad \forall t, w \tag{5.6c}$$

$$P_{itw}\left(\boldsymbol{q}_{itw}\right) \leq P^{\text{cap}} \quad : \quad \mu^{\text{sg,cap}}_{nitw} \quad \forall t, w \tag{5.6d}$$

where q^{sg}_{nitw} is the generation level of the nth synchronous generator in node i at time t under scenario w, Q^{sg}_{ni} and c^{sg}_{ni} are the capacity and the short term marginal cost of the nth synchronous generator in node i, respectively. The constraints (5.6b) and (5.6c) ensure that the ramping limitations of the nth synchronous generator in node i are always met. The nth synchronous generator in node i acts as a strategic firm in the market if γ^{sg}_{ni} is equal to zero and acts as a regulated firm if γ^{sg}_{ni} is equal to one.

Transmission Firms

The Bayes-NE strategy of the transmission firm between nodes i and j is determined by solving the following optimization problem:

$$\max_{\left\{q^{\text{tr}}_{jitw}, q^{\text{tr}}_{ijtw}\right\}_{tw}} \sum_{w} \Psi_w \sum_{t=1}^{N_{\text{T}}} \left(1-\gamma^{\text{tr}}_{ij}\right)\left(P_{jtw}\left(\boldsymbol{q}_{jtw}\right) q^{\text{tr}}_{jitw} + P_{itw}\left(\boldsymbol{q}_{itw}\right) q^{\text{tr}}_{ijtw}\right)$$

$$+\gamma^{\text{tr}}_{ij}\left(\frac{P_{jtw}\left(\boldsymbol{q}_{jtw}\right)}{-\beta_{jt}}+\frac{P_{itw}\left(\boldsymbol{q}_{itw}\right)}{-\beta_{it}}\right)$$

s.t.

$$q^{\text{tr}}_{ijtw}=-q^{\text{tr}}_{jitw} \quad : \quad \mu^{\text{tr}}_{ijtw} \quad \forall t,w \tag{5.7a}$$

$$-Q^{\text{tr}}_{ij}\leq q^{\text{tr}}_{ijtw}\leq Q^{\text{tr}}_{ij} \quad : \quad \mu^{\text{tr,min}}_{ijtw},\mu^{\text{tr,max}}_{ijtw} \quad \forall t,w \tag{5.7b}$$

$$P_{ktw}\left(\boldsymbol{q}_{ktw}\right)\leq P^{\text{cap}}:\mu^{\text{tr,cap}}_{kk'tw} \quad k,k'\in\{i,j\},k\neq k' \quad \forall t,w \tag{5.7c}$$

where q^{tr}_{ijtw} is the electricity flow from nodes j to i at time t under scenario w, and Q^{tr}_{ij} is the capacity of the transmission line between node i and node j. The transmission firm between nodes i and j behaves as a strategic player when γ^{tr}_{ij} is equal to zero and behaves as a regulated player when γ^{tr}_{ij} is equal to one. Note that the term $P_{jtw}\left(\boldsymbol{q}_{jtw}\right)q^{\text{tr}}_{jitw}+P_{itw}\left(\boldsymbol{q}_{itw}\right)q^{\text{tr}}_{ijtw}$ in the objective function of the transmission firm is equal to $(P_{jtw}\left(\boldsymbol{q}_{jtw}\right)-P_{itw}\left(\boldsymbol{q}_{itw}\right))q^{\text{tr}}_{jitw}$ which implies that the transmission firm between two nodes makes profit by transmitting electricity from the node with lower market price to the node with higher market price. Moreover, the price difference between the paired nodes indicates the congestion on the transmission lines and can be used to set the value of Financial Transmission Rights (FTR) [84] in electricity markets.

Transmission lines or interconnectors are usually controlled by the market operator and are regulated to maximize the social welfare in the market. The markets with regulated transmission firms are discussed as electricity markets with transmission constraints in the literature, e.g., see [20,31,35]. However, some electricity markets allow the transmission lines to act strategically, i.e. to make revenue by trading electricity across the nodes [78].

5.3 Solution Approach

In this section, we first provide a game-theoretic analysis of the lower-level problem. Next, the bi-level price volatility management problem is transformed to a single optimization Mathematical Problem with Equilibrium Constraints (MPEC).

5.3.1 Game-theoretic Analysis of the Lower-level Problem

To solve the lower-level problem, we need to study the best response functions of firms participating in the market. Then, any intersection of the best response functions of all firms in all scenarios will be a Bayes-NE. In this subsection, we first establish the existence of Bayes-NE for the lower-level problem. Then, we provide the necessary and sufficient conditions which can be used to solve the lower-level problem.

To transform the bi-level price volatility management problem to a single level problem, we need to ensure that for every vector of storage capacities, *i.e.* $\boldsymbol{Q}^{\text{st}} = [Q_1^{\text{st}}, \cdots, Q_I^{\text{st}}]^\top \geq \mathbf{0}$, the lower-level problem admits a Bayes-NE. At the Bayes-NE strategy of the lower-level problem, no single firm has any incentive to unilaterally deviate its strategy from its Bayes-NE strategy. Note that the objective function of each firm is quasi-concave in its strategy and constraint set of each firm is closed and bounded for all $\boldsymbol{Q}^{\text{st}} = [Q_1^{\text{st}}, \cdots, Q_I^{\text{st}}]^\top \geq \mathbf{0}$. Thus, the lower level game admits a Bayes-NE. This result is formally stated in Proposition 5.2.

Proposition 5.2. *For any vector of storage capacities,* $\boldsymbol{Q}^{\text{st}} = [Q_1^{\text{st}}, \cdots, Q_I^{\text{st}}]^\top \geq \mathbf{0}$*, the lower level game admits a Bayes-NE.*

Proof: Note that the objective function of each firm is continuous and quasi-concave in its strategy. Also, the strategy space is non-empty, compact and convex. Therefore, according to Theorem 1.2 in [79], the lower level game admits a Bayes-NE. ■

Best responses of wind firm *mi*

Let $\boldsymbol{q}_{-(mi)}$ be the strategies of all firms in the market except the wind generator m located in node i. Then, the best response of the wind generator m in node i to $\boldsymbol{q}_{-(mi)}$ satisfies the necessary and sufficient Karush-Kuhn-Tucker (KKT) conditions ($t \in \{1, ..., N_{\text{T}}\}; w \in \{1, ..., N_{\text{w}}\}$):

$$P_{itw}(\boldsymbol{q}_{itw}) + (1 - \gamma_{mi}^{\text{ig}}) \frac{\partial P_{itw}(\boldsymbol{q}_{itw})}{\partial q_{mitw}^{\text{ig}}} q_{mitw}^{\text{ig}} - \frac{\mu_{mitw}^{\text{ig,max}} + \frac{\partial P_{itw}(\boldsymbol{q}_{itw})}{\partial q_{mitw}^{\text{ig}}} \mu_{mitw}^{\text{ig,cap}}}{\Psi_w} \leq 0 \perp q_{mitw}^{\text{ig}} \geq 0 \tag{5.8a}$$

$$q^{\mathrm{ig}}_{mitw} \leq Q^{\mathrm{ig}}_{mitw} \perp \mu^{\mathrm{ig,max}}_{mitw} \geq 0 \tag{5.8b}$$

$$P_{itw}\left(\boldsymbol{q}_{itw}\right) \leq P^{\mathrm{cap}} \perp \mu^{\mathrm{ig,cap}}_{itw} \geq 0 \tag{5.8c}$$

where the perpendicularity sign, $\perp$, means that at least one of the adjacent inequalities must be satisfied as an equality [73].

Best responses of storage firm i

To study the best response of the storage firm in node i, let $\boldsymbol{q}_{-i}$ denote the collection of strategies of all firms except the storage firm in node i. Then, the best response of the storage firm in node i is obtained by solving the following KKT conditions ($t \in \{1, ..., N_{\mathrm{T}}\}; w \in \{1, ..., N_{\mathrm{w}}\}$):

$$P_{itw}\left(\boldsymbol{q}_{itw}\right) + (1-\gamma^{\mathrm{st}}_i)\frac{\partial P_{itw}\left(\boldsymbol{q}_{itw}\right)}{\partial q^{\mathrm{st}}_{itw}} q^{\mathrm{st}}_{itw} + \frac{\mu^{\mathrm{st}}_{itw} - \frac{\partial P_{itw}(\boldsymbol{q}_{itw})}{\partial q^{\mathrm{st}}_{itw}}\mu^{\mathrm{st,cap}}_{itw}}{\Psi_w} = 0 \tag{5.9a}$$

$$\frac{-\eta^{\mathrm{dis}}_i \mu^{\mathrm{st}}_{itw} - \mu^{\mathrm{dis,max}}_{itw} - \Delta \sum_{t'=t}^{N_{\mathrm{T}}}\left(\mu^{\mathrm{st,min}}_{it'w} - \mu^{\mathrm{st,max}}_{it'w}\right)}{\Psi_w} - c^{\mathrm{st}}_i \leq 0 \perp q^{\mathrm{dis}}_{itw} \geq 0 \tag{5.9b}$$

$$\frac{\frac{\mu^{\mathrm{st}}_{itw}}{\eta^{\mathrm{ch}}_i} - \mu^{\mathrm{ch,max}}_{itw} + \Delta \sum_{t'=t}^{N_{\mathrm{T}}}\left(\mu^{\mathrm{st,min}}_{it'w} - \mu^{\mathrm{st,max}}_{it'w}\right)}{\Psi_w} - c^{\mathrm{st}}_i \leq 0 \perp q^{\mathrm{ch}}_{itw} \geq 0 \tag{5.9c}$$

$$q^{\mathrm{st}}_{itw} = \eta^{\mathrm{dis}}_i q^{\mathrm{dis}}_{itw} - \frac{q^{\mathrm{ch}}_{itw}}{\eta^{\mathrm{ch}}_i} \tag{5.9d}$$

$$q^{\mathrm{dis}}_{itw} \leq \zeta^{\mathrm{dis}}_i Q^{\mathrm{st}}_i \perp \mu^{\mathrm{dis,max}}_{itw} \geq 0 \tag{5.9e}$$

$$q^{\mathrm{ch}}_{itw} \leq \zeta^{\mathrm{ch}}_i Q^{\mathrm{st}}_i \perp \mu^{\mathrm{ch,max}}_{itw} \geq 0 \tag{5.9f}$$

$$0 \leq \sum_{t'=1}^{t}\left(q^{\mathrm{ch}}_{it'w} - q^{\mathrm{dis}}_{it'w}\right)\Delta \perp \mu^{\mathrm{st,min}}_{itw} \geq 0 \tag{5.9g}$$

$$\sum_{t'=1}^{t}\left(q^{\mathrm{ch}}_{it'w} - q^{\mathrm{dis}}_{it'w}\right)\Delta \leq Q^{\mathrm{st}}_i \perp \mu^{\mathrm{s,max}}_{itw} \geq 0 \tag{5.9h}$$

$$P_{itw}\left(\boldsymbol{q}_{itw}\right) \leq P^{\mathrm{cap}} \perp \mu^{\mathrm{st,cap}}_{itw} \geq 0 \tag{5.9i}$$

Best responses of synchronous generation firm ni

The best response of the synchronous generator n in node i to $\boldsymbol{q}_{-(ni)}$, i.e. the collection of strategies of all firms except the synchronous generator n in node i, is obtained by solving the following KKT conditions ($t \in \{1, ..., N_\mathrm{T}\}; w \in \{1, ..., N_\mathrm{w}\}$):

$$P_{itw}\left(\boldsymbol{q}_{itw}\right) - c^{\mathrm{sg}}_{ni} + (1-\gamma^{\mathrm{sg}}_{ni})\frac{\partial P_{itw}\left(\boldsymbol{q}_{itw}\right)}{\partial q^{\mathrm{sg}}_{nitw}} q^{\mathrm{sg}}_{nitw} - \frac{\mu^{\mathrm{sg,max}}_{nitw} + \frac{\partial P_{itw}(\boldsymbol{q}_{itw})}{\partial q^{\mathrm{sg}}_{nitw}}\mu^{\mathrm{sg,cap}}_{nitw}}{\Psi_w} + \frac{\mu^{\mathrm{sg,up}}_{ni(t+1)w} - \mu^{\mathrm{sg,up}}_{nitw} + \mu^{\mathrm{sg,dn}}_{nitw} - \mu^{\mathrm{sg,dn}}_{ni(t+1)w}}{\Psi_w} \leq 0 \perp q^{\mathrm{sg}}_{nitw} \geq 0 \tag{5.10a}$$

$$q^{\mathrm{sg}}_{nitw} \leq Q^{\mathrm{sg}}_{ni} \perp \mu^{\mathrm{sg,max}}_{nitw} \tag{5.10b}$$

$$q^{\mathrm{sg}}_{nitw} - q^{\mathrm{sg}}_{ni(t-1)w} \leq R^{\mathrm{up}}_{ni} Q^{\mathrm{sg}}_{ni} \perp \mu^{\mathrm{sg,up}}_{nitw} \geq 0 \tag{5.10c}$$

$$q^{\mathrm{sg}}_{ni(t-1)w} - q^{\mathrm{sg}}_{nitw} \leq R^{\mathrm{dn}}_{ni} Q^{\mathrm{sg}}_{ni} \perp \mu^{\mathrm{sg,dn}}_{nitw} \geq 0 \tag{5.10d}$$

$$P_{itw}\left(\boldsymbol{q}_{itw}\right) \leq P^{\mathrm{cap}} \perp \mu^{\mathrm{sg,cap}}_{nitw} \geq 0 \tag{5.10e}$$

Best responses of transmission firm ij

Finally, the best response of the transmission firm between nodes i and j, to $\boldsymbol{q}_{-(ij)}$, i.e. the set of all firms' strategies except those of the transmission line between nodes i and j, can be obtained using the KKT conditions ($t \in \{1, ..., N_\mathrm{T}\}; w \in \{1, ..., N_\mathrm{w}\}$):

$$P_{itw}\left(\boldsymbol{q}_{itw}\right) + \left(1-\gamma^{\mathrm{tr}}_{ij}\right)\frac{\partial P_{itw}\left(\boldsymbol{q}_{itw}\right)}{\partial q^{\mathrm{tr}}_{ijtw}} q^{\mathrm{tr}}_{ijtw} + \frac{\mu^{\mathrm{tr}}_{jitw} + \mu^{\mathrm{tr}}_{ijtw} + \mu^{\mathrm{tr,min}}_{ijtw} - \mu^{\mathrm{tr,max}}_{ijtw} - \frac{\partial P_{itw}(\boldsymbol{q}_{itw})}{\partial q^{\mathrm{tr}}_{ijtw}}\mu^{\mathrm{tr,cap}}_{ijtw}}{\Psi_w} = 0 \tag{5.11a}$$

$$q^{\mathrm{tr}}_{ijtw} = -q^{\mathrm{tr}}_{jitw} \tag{5.11b}$$

$$-Q^{\mathrm{tr}}_{ij} \leq q^{\mathrm{tr}}_{ijtw} \perp \mu^{\mathrm{tr,min}}_{ijtw} \geq 0 \tag{5.11c}$$

$$q^{\mathrm{tr}}_{ijtw} \leq Q^{\mathrm{tr}}_{ij} \perp \mu^{\mathrm{tr,max}}_{ijtw} \geq 0 \tag{5.11d}$$

$$P_{itw}\left(\boldsymbol{q}_{itw}\right) \leq P^{\mathrm{cap}} \perp \mu^{\mathrm{tr,cap}}_{ijtw} \geq 0 \tag{5.11e}$$

5.3.2 The Equivalent Single-level Problem

Here, the bi-level price volatility management problem is transformed into a single-level MPEC. To this end, note that for every vector of storage capacities the market price can be obtained by solving the firms' KKT conditions. Thus, by imposing the KKT conditions of all firms as constraints in the optimization problem (5.2), the price volatility management problem can be written as the following single-level optimization problem:

$$\min \sum_{i=1}^{I} Q_i^{\mathrm{st}} \tag{5.12}$$

$$\begin{aligned}
&\text{s.t.}\\
&(5.2a-5.2b), (5.8a-5.8c), (5.9a-5.9i), (5.10a-5.10e), (5.11a-5.11e)\\
&m \in \{1, ..., N_i^{\mathrm{ig}}\}, n \in \{1, ..., N_i^{\mathrm{sg}}\}, i, j \in \{1, ..., I\},\\
&t \in \{1, ..., N_{\mathrm{T}}\}; w \in \{1, ..., N_{\mathrm{w}}\}
\end{aligned}$$

where the optimization variables are the storage capacities, the bidding strategies of all firms and the set of all Lagrange multipliers. Because of the nonlinear complementary constraints, the feasible region is not necessarily convex or even connected. Therefore, increasing the storage capacities stepwise, ΔQ^{st}, we solve the lower level problem, which is convex.

Remark: It is possible to convert the equivalent single level problem (5.12) to a Mixed-Integer Non-Linear Problem (MINLP). However, the large number of integer variables potentially makes the resulting MINLP computationally infeasible.

The MPEC problem (5.12) can be solved using extensive search when the number of nodes is small. For large electricity networks, the greedy algorithm proposed in [85] can be used to find the storage capacities iteratively while the other variables are calculated as the solution of the lower level problem. In each iteration, the lower level problem is solved as a Mixed Complementarity Problem (MCP) [86], which is sometimes termed as rectangular variational inequalities. The optimization solution method is illustrated in Algorithm 1. The storage capacity variable is discretized and the increment storage capacity of ΔQ^{st} is added to the selected node i^* at each iteration of the algorithm. Once the price volatility constraint is satisfied with equality, the optimum solution is found.

Although our greedy algorithm just guarantees a locally optimal storage capacity, we obtained the same results in NEM market using the extensive search.

Algorithm 1 The greedy algorithm for finding the storage allocation

while $\max_{it} \mathrm{Var}(P_{itw}(\boldsymbol{q}^{\star}_{itw})) > \sigma_0^2$ **do**
  iteration=iteration+1
  for $i' = 1 : I$ **do**
    $Q^{\mathrm{st}}_{i'}(\text{iteration}) \leftarrow \mathrm{Q}^{\mathrm{st}}_{\mathrm{i'}}(\text{iteration} - 1) + \triangle \mathrm{Q}^{\mathrm{st}}$
    $Q^{\mathrm{st}}_{-i'}(\text{iteration}) \leftarrow \mathrm{Q}^{\mathrm{st}}_{-\mathrm{i'}}(\text{iteration} - 1)$
    $\boldsymbol{q}^{\star} \leftarrow$ Lower level problem Bayes–NE
    Price Volatility$(i') \leftarrow \max_{it} \mathrm{Var}(P_{itw}(\boldsymbol{q}^{\star}_{itw}))$
  end for
  $i^{*} \leftarrow \underset{i}{\text{find}}(\min(\text{Price Volatility(i)}))$
  $Q^{\mathrm{st}}_{i^{*}}(\text{iteration}) \leftarrow \mathrm{Q}^{\mathrm{st}}_{\mathrm{i}^{*}}(\text{iteration} - 1) + \triangle \mathrm{Q}^{\mathrm{st}}$
end while

5.4 Case Study and Simulation Results

In this section, we apply our price volatility management framework to two different types of electricity markets: (*i*) the NEM market, which has a regional pricing mechanism, (*ii*) a 30-bus electricity system with a Locational Marginal Pricing (LMP) mechanism [87]. The most important difference between LMP and regional pricing markets is the number of settlement prices. Tens or hundreds of pricing nodes may be required to implement a LMP market whereas in a regional pricing only few settlement prices are considered. Note that the optimization problem (5.12) can model both regional and LMP markets.

5.4.1 Simulations in NEM

In this subsection, we study the impact of storage installation on price volatility in two nodes of Australia's National Electricity Market (NEM), South Australia (SA) and Victoria (VIC), with regional pricing mechanism, which sets the marginal value of demand at each region as the regional prices. SA has a high level of wind penetration and VIC has high coal-fueled synchronous generation. Real data for price and demand from the year 2015 is used to calibrate the inverse demand function in the model. Different types of generation firms, such as coal, gas, hydro, wind and biomass, with generation capacity (intermittent and dispatchable) of 3.7 GW and 11.3 GW were active in SA and VIC, respectively, in 2015. The transmission line interconnecting SA and VIC, which is a regulated line, has the capacity of 680 MW but currently is working with just 70% of its capacity. The generation capacities in our numerical results are gathered from Australian Electricity Market Operator's (AEMO's) website (aemo.com.au) and all the prices are shown in Australian dollar.

In our study, we consider a set of scenarios each representing a 24-hour wind power availability profile. In order to guarantee a high level of accuracy, we do not employ scenario reduction methods [80] and instead consider 365 daily wind power availability scenarios, with equal probabilities, using the realistic data from the year 2015 in different regions of NEM (source of data: AEMO). Fig. 5.1 shows the hourly wind power availability in SA. On each box in Fig. 5.1, the central mark indicates the average level and the bottom and top edges of the box indicate the 25th and 75th percentiles of wind power availability from the 365 scenarios, respectively. It can be seen that in SA the wind power capacity is about 1200 MW and the wind capacity factor is about 33-42% at different hours.

In what follows, by price volatility we mean the maximum variance of market price, i.e. $\max_{it} \mathrm{Var}(P_{itw}(\boldsymbol{q}^{\star}_{itw}))$. Also, by square root of price volatility we mean the maximum standard deviation of market price, i.e. $\max_{it} \sqrt{\mathrm{Var}(P_{itw}(\boldsymbol{q}^{\star}_{itw})}$.

One-region model simulations in South Australia

In our one-region model simulations, we first study the impacts of peak demand levels and supply capacity shortage on the standard deviation of hourly electricity prices (or square root of hourly price volatilities) in SA with no storage. Next, we study the effect of storage on the price volatility in SA. Fig. 5.2 shows the average and standard deviation of hourly prices for a day in SA (with no storage) for three different cases: (*i*) a regular demand day, (*ii*) a high demand day, (*iii*) a high demand day with coal-plant outage.

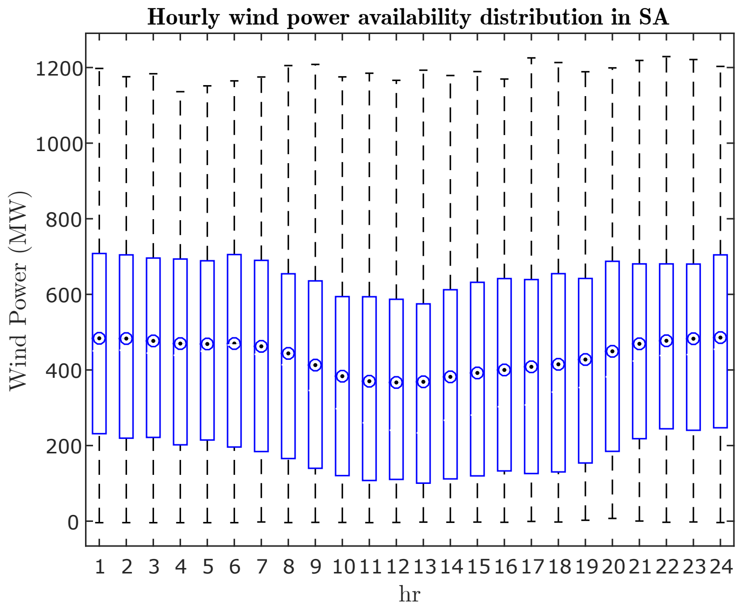

Figure 5.1: SA's Hourly wind power availability distribution in 2015 (the central marks show the average levels and the bottom and top edges of the boxes indicate the 25th and 75th percentiles).

An additional load of 1000 MW is considered in the high demand case during hours 16, 17 and 18 to study the joint effect of wind intermittency and large demand variations on the price volatility. The additional loads are sometimes demanded in the market due to unexpected high temperatures happening in the region. The coal-plant outage case is motivated by the recent retirement of two coal-plants in SA with total capacity of 770 MW [88]. This allows us to investigate the joint impact of wind indeterminacy and low base-load generation capacity on the price volatility.

According to Fig. 5.2, wind power fluctuation does not create much price fluctuation in a regular demand day. The square root of the price volatility in the regular demand day is equal to 65 \$/MWh. Depending on the wind power availability level, the peak price varies from 92 \$/MWh to 323 \$/MWh, with average of 210 \$/MWh, in a regular demand day. Based on Fig. 5.2, the square root of the price volatility in the high demand day is equal to 1167 \$/MWh. The maximum price in a high demand day in SA changes from 237 \$/MWh to 4466 \$/MWh, with average of 1555 \$/MWh, because of wind power availability fluctuation. The extra load at peak times and the wind power fluctuation create a higher level of price volatility during a high demand day compared with a regular demand day.

The retirement (outage) of coal-plants in SA beside the extra load at peak hours increases the price volatility due to the wind power fluctuation. The maximum price during the high demand day with coal-plant outage varies from 377 \$/MWh to the cap price of 11000 \$/MWh, with average of 5832 \$/MWh. The square root of the price volatility during the high demand day with coal-plant outage is equal to 4365 \$/MWh. The square root of the price volatility during the high demand day with coal-plant outage is almost 67 times more than the regular demand day due to the simultaneous variation in both supply and demand.

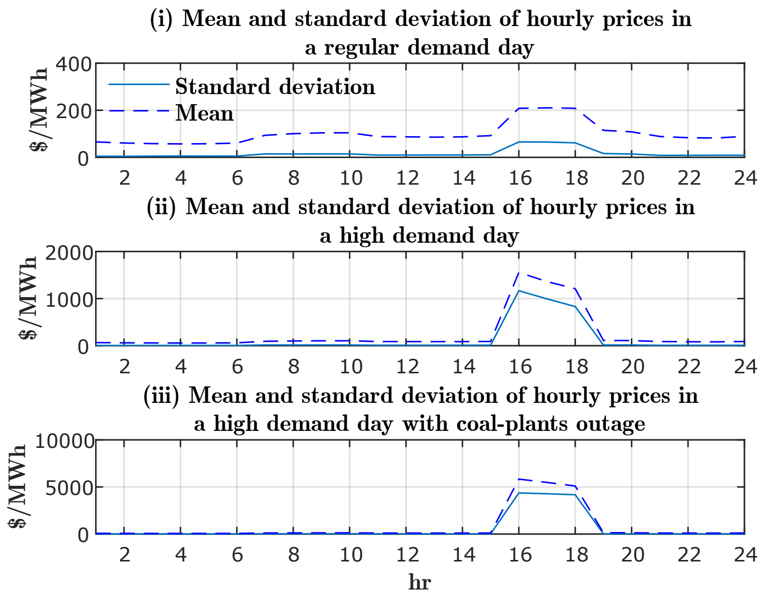

Figure 5.2: Standard deviation and mean of hourly wholesale electricity prices in SA with no storage.

Fig. 5.3 shows the minimum required (strategic/regulated) storage capacities for achieving various levels of price volatility in SA during a high demand day with coal-plant outage. The minimum storage capacities are calculated by solving the optimization problem (5.12) for the high demand day with coal-plant outage case. According to Fig. 5.3, a strategic storage firm requires a substantially larger capacity, compared with a regulated storage firm, to achieve a target price volatility level due to the selfish behavior of the storage firms. In fact, the strategic storage firms may sometimes withhold their available capacities and do not participate in the price volatility reduction as they do not always benefit from reducing the price. The price volatility in SA can be reduced by 50% using either 530 MWh strategic storage or 430 MWh regulated storage. Note that AEMO has forecasted about 500 MWh battery storage to be installed in SA until 2035 [89].

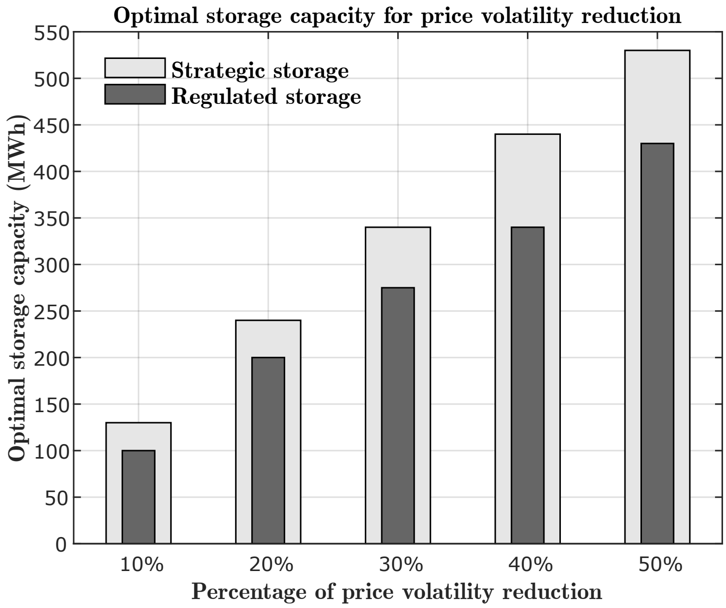

Figure 5.3: Optimal strategic and regulated storage capacity for achieving different price volatility levels in SA region for a high demand day with coal-plant outage.

According to our numerical results, storage can displace the peaking generators, with high fuel costs and market power, which results in reducing the price level and the price volatility. A storage capacity of 500 MWh (or 500 MW given the discharge coefficient $\eta^{\text{dis}} = 1$) reduces the square root of the price volatility from 4365 \$/MWh to 2692 \$/MWh, almost 38% reduction, during a high demand day with coal-plant outage in SA.

The behaviour of the peak and the daily average prices for the high demand day with coal-plant outage in SA is illustrated in Fig. 5.4. In this figure, the peak price represents the average of highest prices over all scenarios during the day, i.e. $\sum_w \Psi_w \left(\max_t P_{tw}(\boldsymbol{q}^{\star}_{tw})\right)$ and the daily average price indicates the average of price over time and scenarios, i.e. $\frac{1}{N_T} \sum_{tw} P_{tw}(q^{\star}_{tw})\Psi_w$. Sensitivity analysis of the peak and the daily average prices in SA with respect to storage capacity indicates that high storage capacities lead to relatively low prices in the market. At very high prices, demand is almost inelastic and a small amount of excess supply leads to a large amount of price reduction. According to Fig. 5.4, the rate of peak price reduction decreases as the storage capacity increases since large storage capacities lead to lower peak prices which make the demand more elastic.

Based on Fig. 5.4, the impact of storage on the daily average and peak prices depends on whether the storage firm is strategic or regulated. It can be observed that the impacts of strategic and regulated storage firms on the daily peak/average prices are almost similar for small storage capacities, i.e. when the storage capacity is smaller than 100 MWh (or 100 MW given $\eta^{\text{dis}} = 1$). However, a regulated firm reduces both the peak and the average prices more efficiently compared with a strategic storage firm as its capacity becomes large. A large strategic storage firm in SA does not use its excess capacity beyond 500 MWh to reduce the market price since it acts as a strategic profit maximizer, but a regulated storage firm contributes to the price volatility reduction as long as there is potential for price reduction by its operation.

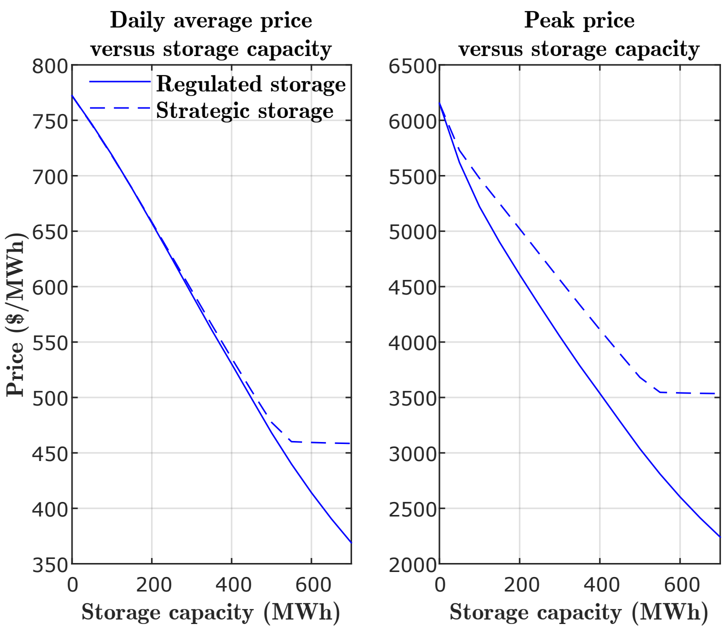

Figure 5.4: Daily peak and average prices in SA versus storage capacity in a high demand day with coal-plant outage.

Fig. 5.5 depicts the square root of price volatility versus storage capacity in SA during the high demand day with coal-plant outage. According to this figure, the price volatility in the market decreases by installing either regulated or strategic storage devices. To reduce the square root of price volatility to 3350 \$/MWh, the required strategic capacity is about 100 MWh more than that of a regulated storage. Moreover, a strategic storage firm stops reducing the price volatility when its capacity exceeds a threshold value. In our study, a strategic storage firm does not reduce the square root of price volatility more than 32%, but a regulated firm reduces it by 89%. These observations confirm that regulated storage firms are more efficient than strategic firms in reducing the price volatility.

The impact of the regulated storage firm in reducing the price volatility can be divided into three ranges of initial, efficient, and saturated, as shown in Fig. 5.5. In the initial range, an increment in the capacity of the regulated firm slightly reduces the price volatility. Then the price volatility reduces sharply with storage capacity in the second region. Finally, the price volatility reduction gradually stops in the saturated region. This observation implies that although storage alleviates the price volatility in the market, it is not capable to eliminate it completely.

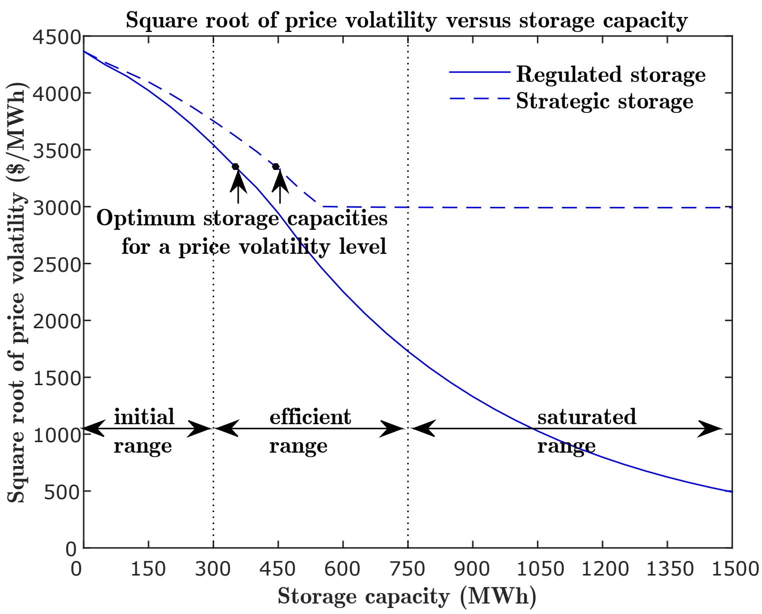

Figure 5.5: Square root of price volatility in SA versus storage capacity during a high demand day with coal-plant outage.

Two-region model simulations in South Australia and Victoria

In the one-region model simulations, we analysed the impact of storage on the price volatility in SA when the SA-VIC interconnector is not active. In this subsection, we first study the effect of the interconnector between SA and VIC on the price volatility in the absence of storage firms. Next, we investigate the impact of storage firms on the price volatility when the SA-VIC transmission line operates at various capacities. In our numerical results, SA is connected to VIC using a 680 MW interconnector which is currently operating with 70% of its capacity, i.e. 30% of its capacity is under maintenance. The numerical results in this subsection are based on the two-node model for a high demand day with coal-plant outage in SA. To investigate the impact of transmission line on price volatility, it is assumed that the SA-VIC interconnector operates with 60% and 70% of its capacity.

According to our numerical results, the peak price (the average of highest prices over all scenarios) in SA is equal to 6154 \$/MWh when the SA-VIC interconnector is completely in outage. However, the peak price reduces to 3328 \$/MWh and 2432 \$/MWh when the interconnector operates at 60% and 70% of its capacity. The square root of price volatility is 4365 \$/MWh, 860 \$/MWh, and 614 \$/MWh when the capacity of the SA-VIC transmission line is equal to 0%, 60%, and 70%, respectively, which emphasizes the importance of interconnectors in price volatility reduction.

Simulation results show that as long as the interconnector is not congested, the line alleviates the price volatility phenomenon in SA by importing electricity from VIC to SA at peak times. Since the market in SA compared to VIC is much smaller, about three times, the price volatility abatement in SA after importing electricity from VIC is much higher than the price volatility increment in VIC. Moreover, the price volatility reduces as the capacity of transmission line increases.

Fig. 5.6 shows the optimum storage capacity versus the percentage of price volatility reduction in the two-node market. According to our numerical results, storage is just located in SA, which witnesses a high level of price volatility as the capacity of transmission line decreases. According to this figure, the optimum storage capacity becomes large as the capacity of transmission line decreases. Note that a sudden decrease of the transmission line capacity may result in a high level of price volatility in SA. However, based on Fig. 5.6, storage firms are capable of reducing the price volatility during the outage of the interconnecting lines.

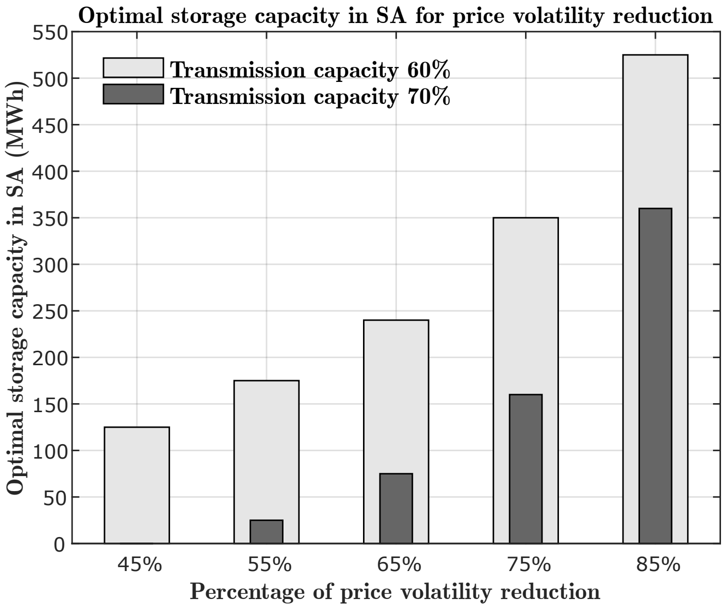

Figure 5.6: Optimal regulated storage capacity versus the percentage of price volatility reduction in the two-node market in a high demand day with coal-plant outage in SA.

5.4.2 Simulations for a 30-bus System

In order to assess the functionality of our optimal storage allocation model for markets consisting relatively high number of nodes, we simulate a standard IEEE 30-bus (30-node) electricity network with LMP pricing mechanism, which sets the marginal value of demand at each bus or node as the nodal prices, in this subsection. The generation and transmission data is based upon [90], which includes six synchronous generators introduced in Table 5.1. We assume the first two generators are regulated in our system. To consider the impact of supply scarcity, we retire the synchronous generator at node 5 and install the wind power generation capacity of 2.5 MW at each node, i.e., the total capacity of 75 MW in the system, in our study. The transmission line limits are set to 50%

of their values so that some lines would be binding in the solutions.

Table 5.1: Location, capacity and generation cost of synchronous generators in the 30-bus electricity system.

Unit	1	2	3	4	5	6
Bus	1	2	5	8	11	13
Capacity (MW)	200	80	50	35	30	40
Cost ($/MWh)	15	15	35	35	35	35

We divide a day into the off-peak period (10 hours), the peak period (4 hours) and the shoulder period (10 hours) times. The demand in the off-peak is 10% more than the demand in the shoulder period whereas the peak demand is 25% more than the shoulder demand. Given the demand values in [90], we assume the electricity prices are equal to 40, 75 and 50 $/MWh during off-peak, peak, and shoulder periods, respectively.

In the absence of storage, the square root of the price volatility is equal to 250 $/MWh in the market due to the joint effect of wind power fluctuation and the power-plant retirement. To compute the storage capacity, we use Algorithm 1 with the increment storage capacity of 15 MWh. According to our numerical results, Algorithm 1 installs the storage only at node 5, which is the highest price volatile node in the system, in order to meet the required price volatility level. Fig (5.7) represents the price volatility level after allocating the storage capacity, calculated by the greedy algorithm 1. The step size of the increment storage capacity is considered as 15 MWh in each iteration of the algorithm. For instance, the total storage capacity of 60 MWh at the node 5 is calculated to address the square root of the price volatility limit of 90 $/MWh. The joint effect of capacity retirement and high electricity demand at node 5 leads to high level of price volatility after installing the intermittent wind power capacities in the market and makes the node 5 the likely candidate for storage allocation to meet the price volatility requirement.

5.5 Conclusion

High penetration of intermittent renewables, such as wind or solar farms, brings high levels of price volatility in electricity markets. Our study presents an optimization model which decides on the minimum storage capacity required for achieving a price volatility

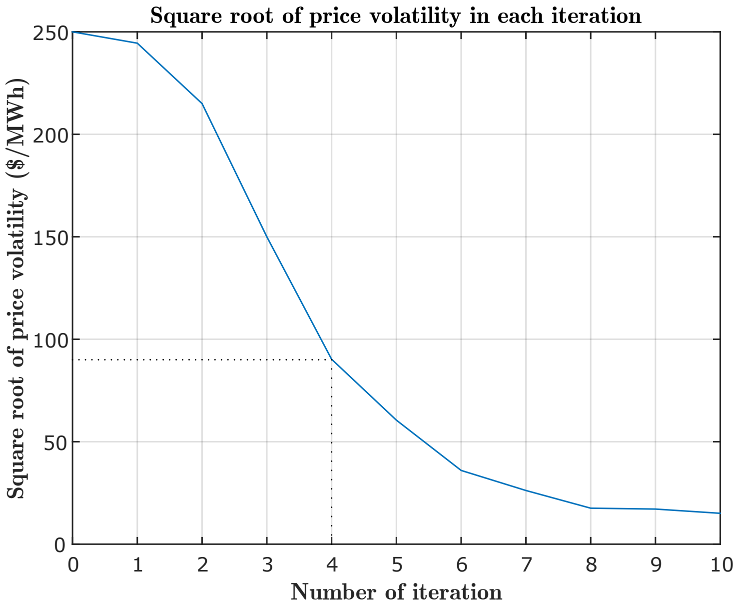

Figure 5.7: Square root of price volatility level in the 30-bus system after ten iterations of Algorithm 1 with $\Delta Q^{st} = 15$MWh.

target in electricity markets. Based on our numerical results, the impact of storage on the price volatility in one-node electricity market of SA, two-node market of SA-VIC and the standard 30-bus IEEE system can be summarized as:

- Storage alleviates price volatility in the market due to the wind intermittency. However, storage does not remove price volatility completely, i.e. storage stops reducing the price volatility when it is not profitable.

- The effect of a storage firm on price volatility reduction depends on whether the firm is regulated or strategic. Both storage types have similar operation behaviour and price reduction effect when they possess small capacities. For larger capacities, a strategic firm may under-utilize its available capacity and stop reducing the price level due to its profit maximization strategy. On the other hand, a regulated storage firm is more efficient in price volatility reduction because of its social welfare maximization strategy. The price level and volatility reduction patterns observed when storage firms are regulated provide stronger incentives for the market operator to subsidize the storage technologies.

- Both storage devices and transmission lines are capable of reducing the price volatility. High levels of price volatility that may happen due to the line maintenance can be alleviated by storage devices.
- Although many parameters affect the price volatility level of a system, penetration of intermittent wind power generation in a region makes the region or node highly price volatile when a synchronous generation capacity outage happens or high load level is demanded.

Although we showed in this chapter that storage can reduce the average price and price volatility levels in the market, we study how the mixtures of wind and storage capacities affect the electricity market prices in Chapter 6.

Chapter 6

Regulated Wind-Storage to Reduce the Electricity Market Price and Volatility

This chapter investigates the impacts of optimal regulated wind and electricity storage allocation on the average price and the price volatility in electricity markets. A stochastic bi-level optimization model is proposed for optimal sizing of wind and battery capacities to minimize a wighted sum of the average market price and price volatility. A fixed budget is allocated on wind and battery capacities in an upper level problem. The operation of strategic/regulated generation, storage and transmission players is simulated in a lower level problem using a stochastic (Bayesian) Cournot-based game model. The Australia's National Electricity Market (NEM), which is experiencing occasional price peaks due to closure of a 1600 MW coal power plant and gas price surge, is considered as the case study. Our simulation results show that investment on regulated wind is more efficient in reducing the average price, while investment on regulated storage is more effective in price volatility reduction. A mixture of wind and storage is optimal in minimizing the weighted sum of both average price and price volatility.

6.1 Introduction

IN THIS chapter, a bi-level stochastic optimization model is proposed for optimal sizing of regulated wind and storage capacities in a single region (node) to minimize the weighted sum of average price and price volatility taking into account interdependencies between regions in a wholesale multi-region electricity market. NEM is used as a case study and a detailed numerical analysis conducted. Our simulation results show that investment on regulated wind is more efficient in reducing the average price, while investment on regulated storage is more effective in price volatility reduction.

The contributions of this chapter are summarized as follows:

- A bi-level optimization model is proposed to optimally allocate a fixed budget between regulated wind and storage capacities in a single region to minimize the weighted sum of average price and price volatility, considering nodal interdependencies.
- In the upper level problem, the weighted sum of average price and price volatility in the specified region is minimized by allocating a fixed budget on regulated wind and storage capacities in that region.
- In the lower level problem, the non-cooperative interaction between strategic and regulated generation, storage and transmission players in the market is modeled as a stochastic (Bayesian) Cournot-based game. The equilibrium prices at the lower level problem, which are calculated based on nonlinear inverse demand functions, are functions of the regulated wind and storage capacities.
- Considering regulated firms in addition to strategic firms distinguishes our model in the lower level problem from a standard Cournot game.
- The transmission lines are modeled as profit maximizer market players in our developed multi-region electricity market model in the lower level problem. Finding the equilibrium point is computationally far more convenient in electricity market models with profit maximizer transmission players [91] than in electricity market models which consider the transmission lines as constraints for their clearing engines [34].
- The existence of Bayesian Nash Equilibrium (Bayes-NE) [81] is established for the lower level problem, which includes nonlinear inverse demand functions.

The rest of this chapter is organized as follows. Section 6.2 illustrates the system model and the proposed bi-level optimization problem. The solution approach for finding the market equilibrium is presented in Section 6.3. Section 6.4 provides the simulation results and Section 6.5 presents the concluding remarks.

6.2 The Problem and Market Model

We consider a regional electricity market including $\{1, ..., N_I\}$ regions (nodes). Let $\mathcal{N}_i^{\text{wg}}$ be the set of intermittent generation firms located in node i, $\mathcal{N}_i^{\text{sg}}$ be the set of synchronous generators, such as coal, gas, and hydro power plants, located in node i, $\mathcal{N}_i^{\text{s}}$ be the set of storage firms, such as pump-hydro and battery, located in node i, and $\mathcal{N}_i^{\text{tr}}$ be the set of neighboring nodes of the node i. Since some parameters such as wind and solar power availabilities, which affect the electricity generation, are stochastic, a scenario-based model including N_W different scenarios is developed to model the intermittent power generation in the electricity network. The strategies of intermittent and synchronous generators, storage firms, and transmission players as well as the nodal prices are determined by solving a stochastic (Bayesian) Cournot-based game.

In this chapter, we present a bi-level optimization framework for optimally allocating a budget on regulated capacities of wind and storage to minimize the weighted sum of average price and price volatility in a single node taking into account the interdependencies to other nodes in the market. All the market players, which are allowed to be strategic or regulated, with their decision variables, operating limits, and objective functions are introduced in detail in the lower level problem, Section 6.2.2.

6.2.1 Upper-level Problem

In the upper-level optimization problem, we minimize the weighted sum of average price and its standard deviation over the operation horizon $\{1, ..., N_T\}$ and scenario set $\{1, ..., N_W\}$ at node $i^* \in \{1, ..., N_I\}$ by allocating a fixed budget on regulated storage and wind generation technologies. The price volatility is measured by the nodal price variance. Market price variance and mean in node i^* under a set of scenarios $\{1, ..., N_W\}$, i.e., $\mathsf{Var}\left(\{P_{i^*tw}\}_w\right)$ and $\mathsf{E}\left(\{P_{i^*tw}\}_w\right)$, are defined as:

$$\mathsf{Var}\left(\{P_{i^*tw}\}_w\right) = \sum_w \left(P_{i^*tw}\left(.\right)\right)^2 \Psi_w - \left(\sum_w P_{i^*tw}\left(.\right) \Psi_w\right)^2 \tag{6.1a}$$

$$\mathsf{E}\left(\{P_{i^*tw}\}_w\right) = \sum_w P_{i^*tw}\left(.\right)\Psi_w \tag{6.1b}$$

where Ψ_w is the probability of scenario w, and $P_{i^*tw}\left(.\right)$ represents the market price in node i^* at time t under the scenario w, which is a function of the decision variables, i.e., generation, arbitrage and transmission levels, of all players in the lower level problem. $P_{i^*tw}\left(.\right)$ is a probabilistic function because of the stochastic intermittent generation in our model.

Given that the wind and storage technologies have unequal lifespans, we compare their equivalent annual cost and consider the equivalent annual budget in our model. Considering the relation between the investment cost, I, and its equivalent annual cost, $\overline{I}$, for a technology with lifespan of PL, that is, $I = \sum_{y=1}^{\mathrm{PL}} \frac{\overline{I}}{(1+r)^y}$, the equivalent annual costs of wind and storage technologies, $\overline{I^{\mathrm{ig}}}$ and $\overline{I^{\mathrm{s}}}$, become as [92]:

$$\overline{I^{\mathrm{ig}}} = \frac{rI^{\mathrm{ig}}}{1-(1+r)^{-\mathrm{PL}^{\mathrm{ig}}}} \tag{6.2a}$$

$$\overline{I^{\mathrm{s}}} = \frac{rI^{\mathrm{s}}}{1-(1+r)^{-\mathrm{PL}^{\mathrm{s}}}} \tag{6.2b}$$

where I^{ig} and I^{s} are the total investment costs, and $\mathrm{PL}^{\mathrm{ig}}$ and PL^{s} are the life spans of wind and storage technologies, respectively. The parameter r represents the discount rate.

Based on the equivalent annual costs of wind and storage technologies, $\overline{I^{\mathrm{ig}}}$ and $\overline{I^{\mathrm{s}}}$, $\overline{I^{\mathrm{s}}}Q_{i^*}^{\mathrm{s,reg}}$ and $\overline{I^{\mathrm{ig}}}Q_{i^*}^{\mathrm{ig,reg}}$ represent the investment share from the equivalent annual budget, $\overline{\mathrm{B}}$, on wind and storage, respectively.

Given the equations for price volatility and average price (6.1a-6.1b), which are functions of the strategy of all firms, and the equations for the equivalent annual cost of wind and storage technologies (6.2a-6.2b), we define the upper level optimization problem as:

$$\min_{Q_{i^*}^{\mathrm{ig,reg}},Q_{i^*}^{\mathrm{s,reg}}} (1-k)\sqrt{\mathsf{Var}\left(\{P_{i^*tw}\}_{tw}\right)} + k\overline{\mathsf{E}}\left(\{P_{i^*tw}\}_{tw}\right) \tag{6.3a}$$

s.t.

$$\overline{I^{\mathrm{s}}}Q_{i^*}^{\mathrm{s,reg}} + \overline{I^{\mathrm{ig}}}Q_{i^*}^{\mathrm{ig,reg}} = \overline{\mathrm{B}}\$ \tag{6.3b}$$

where $0 \leq k \leq 1$ represents the weighting coefficient, $Q_{i^*}^{\text{ig,reg}}$ is the regulated wind generation capacity and $Q_{i^*}^{\text{s,reg}}$ is the regulated storage capacity in node i^*. $\overline{\mathsf{Var}}\left(\{P_{i^*tw}\}_{tw}\right)$ is the normalized level of the average of price volatility levels over the horizon $\{1, ..., N_T\}$, i.e., normalized of $\frac{\sum_t \mathsf{Var}(\{P_{i^*tw}\}_w)}{N_T}$, and $\overline{\mathsf{E}}\left(\{P_{i^*tw}\}_{tw}\right)$ is the normalized level of the average of mean prices over the horizon $\{1, ..., N_T\}$, i.e., normalized of $\frac{\sum_t \mathsf{E}(\{P_{i^*tw}\}_w)}{N_T}$. The normalized levels of price volatility and mean price, which are between zero and one, indicate their ratio with respect to their base values, i.e., with respect to their amounts when there is no regulated wind and storage firm in the market.

6.2.2 Lower-level Problem

The lower level problem is similar to the one used in Chapter 5, but differs in including a regulated wind and storage firm in the market.

In the lower level problem, the strategies of all market players and the nodal market prices are obtained by solving a stochastic Cournot-based game between intermittent generators, synchronous generators, storage firms, and transmission firms. Following the standard Cournot game models [30], any player in our model maximizes its objective function given the decision variables of other players. Our game model, which considers different wind and solar power availability scenarios with given probabilities, is consistent with the Bayesian game definition. Players maximize their utility functions over a set of scenarios with a given probability distribution in a Bayesian game [81]. Note that the decision variables in the upper level problem, $Q_{i^*}^{\text{ig,reg}}$ and $Q_{i^*}^{\text{s,reg}}$, are the wind and storage capacity amounts of a regulated wind-storage firm in node i^*.

The market price in node i at time t under scenario w is represented in our model by an exponential inverse demand function [52]:

$$P_{itw}\left(y_{itw}\right) = \alpha_{it} e^{-\beta_{it} y_{itw}} \tag{6.4}$$

where α_{it} and β_{it} are positive real values representing in the price function, and y_{itw} is the net electricity demand in node i at time t under scenario w.

The equality between electricity supply and demand in each node and at any time, i.e., the the nodal electricity balance, is ensured in our model with the following equations:

$$y_{itw} = \sum_{m \in \mathcal{N}_i^{\text{wg}}} q_{mitw}^{\text{ig}} + \sum_{n \in \mathcal{N}_i^{\text{sg}}} q_{nitw}^{\text{sg}} + \sum_{b \in \mathcal{N}_i^{\text{s}}} q_{bitw}^{\text{s}} + \sum_{j \in \mathcal{N}_i^{\text{tr}}} q_{ijtw}^{\text{tr}} \quad \forall i \neq i^* \tag{6.5a}$$

$$y_{itw} = \sum_{m \in \mathcal{N}_i^{\text{wg}}} q_{mitw}^{\text{ig}} + \sum_{n \in \mathcal{N}_i^{\text{sg}}} q_{nitw}^{\text{sg}} + \sum_{b \in \mathcal{N}_i^{\text{s}}} q_{bitw}^{\text{s}} + \sum_{j \in \mathcal{N}_i^{\text{tr}}} q_{ijtw}^{\text{tr}} + q_{itw}^{\text{ig,reg}} + q_{itw}^{\text{s,reg}} \quad i = i^* \tag{6.5b}$$

where q_{mitw}^{ig} is the generation strategy of the mth intermittent generator located in node i, q_{nitw}^{sg} is the generation strategy of the nth synchronous generator located in node i, q_{bitw}^{s} is the charge/discharge strategy of the storage firm b in node i, q_{ijtw}^{tr} is the transmission strategy of line between nodes i and j, and $q_{itw}^{\text{ig,reg}}$ and $q_{itw}^{\text{s,reg}}$ are the wind generation strategy and the storage strategy of the regulated firm in node i^*, respectively, at time t and under scenario w.

In what follows, we use $P_{itw}(.)$ to refer to the market price in (6.4).

Intermittent Generators

The mth intermittent generator (wind or solar) in node i determines its best response strategy by solving the following profit maximization problem:

$$\max_{\left\{q_{mitw}^{\text{ig}}\right\}_{tw} \succeq 0} \sum_{w=1}^{N_{\text{W}}} \Psi_w \sum_{t=1}^{N_{\text{T}}} \left(P_{itw}(.) - c_{mi}^{\text{ig}}\right) q_{mitw}^{\text{ig}} \tag{6.6a}$$

s.t.

$$q_{mitw}^{\text{ig}} \leq \omega_{itw} Q_{mi}^{\text{ig}} \quad \forall t, w \tag{6.6b}$$

$$P_{itw}(.) \leq P^{\text{cap}} \quad \forall t, w \tag{6.6c}$$

where q_{mitw}^{ig} (decision variable) is the generation level of the intermittent generator m in node i at time t under scenario w, Q_{mi}^{ig} is its maximum generation capacity, and c_{mi}^{ig} is its marginal cost of generation. The constraint (6.6b) limits the electricity generation to the available generation capacity of the firm, considering the energy availability coefficient ω_{itw} in node i at time t under scenario w. The constraint (6.6c) ensures that the market price is always less than the cap price P^{cap}.

Synchronous Generators

The best response strategy of the nth synchronous generator in node i is obtained by solving the following profit maximization problem:

$$\max_{\left\{q^{\text{sg}}_{nitw}\right\}_{tw} \succeq 0} \sum_{w=1}^{N_{\text{W}}} \Psi_w \sum_{t=1}^{N_{\text{T}}} \left(P_{itw}\left(.\right) - c^{\text{sg}}_{ni}\right) q^{\text{sg}}_{nitw} \tag{6.7a}$$

s.t.

$$q^{\text{sg}}_{nitw} \le Q^{\text{sg}}_{ni} \quad \forall t, w \tag{6.7b}$$

$$q^{\text{sg}}_{nitw} - q^{\text{sg}}_{ni(t-1)w} \le R^{\text{up}}_{ni} Q^{\text{sg}}_{ni} \quad \forall t, w \tag{6.7c}$$

$$q^{\text{sg}}_{ni(t-1)w} - q^{\text{sg}}_{nitw} \le R^{\text{dn}}_{ni} Q^{\text{sg}}_{ni} \quad \forall t, w \tag{6.7d}$$

$$\sum_t q^{\text{sg}}_{nitw} \le G_{ni} \quad \forall w \tag{6.7e}$$

$$P_{itw}\left(.\right) \le P^{\text{cap}} \quad \forall t, w \tag{6.7f}$$

where q^{sg}_{nitw} (decision variable) is the generation level of the synchronous generator n in node i at time t under scenario w, Q^{sg}_{ni} is its generation capacity, and c^{sg}_{ni} is its marginal cost of generation. The constraint (6.7b) considers the maximum capacity limit and the constraints (6.7c-6.7d) consider the ramping up and down limits, R^{up}_{ni} and R^{dn}_{ni}, respectively. The constraint (6.7e) considers the inter-temporal energy availability G_{ni}, e.g., the total hydro power generation over a year due to the dam water availability during that period.

Storage Firms

The best response strategy of the bth storage firm in node i is the solution of the following profit maximization problem:

$$\max_{\substack{\left\{q^{\text{dis}}_{bitw}, q^{\text{ch}}_{bitw}\right\}_{tw}\succeq 0 \\ ,\left\{q^{\text{s}}_{bitw}\right\}_{tw}}} \sum_{w=1}^{N_{\text{W}}} \Psi_w \sum_{t=1}^{N_{\text{T}}} P_{itw}\left(.\right) q^{\text{s}}_{bitw} - c^{\text{s}}_{bi} \left(q^{\text{dis}}_{bitw} + q^{\text{ch}}_{bitw}\right) \tag{6.8a}$$

s.t.

$$q^{\text{s}}_{bitw} = \eta^{\text{dis}}_{bi} q^{\text{dis}}_{bitw} - \frac{q^{\text{ch}}_{bitw}}{\eta^{\text{ch}}_{bi}} \quad \forall t, w \tag{6.8b}$$

$$q^{\text{dis}}_{bitw} \leq \zeta^{\text{dis}}_{bi} Q^{\text{s}}_{bi} \quad \forall t, w \tag{6.8c}$$

$$q^{\text{ch}}_{bitw} \leq \zeta^{\text{ch}}_{bi} Q^{\text{s}}_{bi} \quad \forall t, w \tag{6.8d}$$

$$0 \leq \sum_{k=1}^{t} \left(q^{\text{ch}}_{bikw} - q^{\text{dis}}_{bikw}\right) \Delta \leq Q^{\text{s}}_{bi} \quad \forall t, w \tag{6.8e}$$

$$P_{itw}\left(.\right) \leq P^{\text{cap}} \quad \forall t, w \tag{6.8f}$$

where q^{ch}_{bitw} and q^{dis}_{bitw} (decision variables) are the charge and discharge levels of the storage firm b in node i at time t under scenario w, respectively, q^{s}_{bitw} (intermediate decision variable) is the net charge/discharge level, c^{s}_{bi} is the marginal cost of charge/discharge, and η^{ch}_{bi} and η^{dis}_{bi} are the charging and discharging efficiencies, respectively. The equality (6.8b) indicates the net outflow or inflow of electricity, the constraints (6.8c) and (6.8d) limit the output/input energy flow of the firm, with coefficients ζ^{dis}_{bi} and ζ^{ch}_{bi}, respectively. The parameters ζ^{ch}_{bi} and ζ^{dis}_{bi} indicate the percentage of the storage capacity Q^{s}_{bi} that can be charged or discharged during time period Δ. The constraint (6.8e) limits the total stored energy to its maximum capacity, assuming that the storage devices are initially fully discharged.

Transmission Firms

The best response strategy of the transmission line (interconnector) between nodes i and j is obtained by solving the following profit maximization problem:

$$\max_{\left\{q^{\text{tr}}_{jitw}, q^{\text{tr}}_{ijtw}\right\}_{tw}} \sum_{w=1}^{N_W} \Psi_w \sum_{t=1}^{N_T} \left(P_{jtw}\left(.\right) q^{\text{tr}}_{jitw} + P_{itw}\left(.\right) q^{\text{tr}}_{ijtw}\right) \left(1 - \gamma^{\text{tr}}_{ij}\right) + \gamma^{\text{tr}}_{ij} \left(\frac{P_{jtw}\left(.\right)}{-\beta_{jt}} + \frac{P_{itw}\left(.\right)}{-\beta_{it}}\right) \tag{6.9a}$$

s.t.

$$q^{\text{tr}}_{ijtw} = -q^{\text{tr}}_{jitw} \quad \forall t, w \tag{6.9b}$$

$$-Q^{\text{tr}}_{ij} \leq q^{\text{tr}}_{ijtw} \leq Q^{\text{tr}}_{ij} \quad \forall t, w \tag{6.9c}$$

$$P_{ktw}\left(.\right) \leq P^{\text{cap}} \quad k \in \{i, j\}, \forall t, w \tag{6.9d}$$

where q^{tr}_{ijtw} (decision variable) is the electricity transmitted from node j to node i at time t under scenario w, and Q^{tr}_{ij} is the capacity of transmission line between nodes i and j. The transmission firm between nodes i and j is a strategic player when γ^{tr}_{ij} is zero and is a regulated player when γ^{tr}_{ij} is one. It is discussed in [52] that maximizing $P_{jt}\left(.\right) q^{\text{tr}}_{jitw} + P_{itw}\left(.\right) q^{\text{tr}}_{ijtw}$ is equal to maximizing the profit from electricity transmission between nodes i and j. Besides, it is shown in Appendix B that maximizing $\frac{P_{jtw}(.)}{-\beta_{jt}} + \frac{P_{itw}(.)}{-\beta_{it}}$ is equivalent to maximizing the social welfare when the transmission firm between nodes i and j is regulated. Note that the electricity markets with regulated transmission firms are called *electricity markets with transmission constraints* in the literature, e.g., [20,35]. The constraint (6.9b) ensures that electricity does not flow simultaneously in both directions of the line, and the constraint (6.9c) limits the electricity flow between nodes i and j to the capacity of the line.

Regulated Wind-Storage Firm

The best response strategy of the regulated wind-storage firm in node i^* is determined by solving the following optimization problem:

$$\max_{\substack{\left\{q^{\text{ig,reg}}_{i^*tw}\right\}_{tw}\succeq 0 \\ ,\left\{q^{\text{dis,reg}}_{i^*tw},q^{\text{ch,reg}}_{i^*tw}\right\}_{tw}\succeq 0 \\ ,\left\{q^{\text{s,reg}}_{i^*tw}\right\}_{tw}}} \sum_{w=1}^{N_{\text{W}}} \Psi_w \sum_{t=1}^{N_{\text{T}}} \frac{P_{i^*tw}\left(.\right)}{-\beta_{i^*t}} - c^{\text{ig,reg}}_{i^*} q^{\text{ig,reg}}_{i^*tw} - c^{\text{s,reg}}_{i^*}\left(q^{\text{dis,reg}}_{i^*tw} + q^{\text{ch,reg}}_{i^*tw}\right) \tag{6.10a}$$

s.t.

$$q^{\text{ig,reg}}_{i^*tw} \leq \omega_{i^*tw} Q^{\text{ig,reg}}_{i^*} \quad \forall t,w \tag{6.10b}$$

$$q^{\text{s,reg}}_{i^*tw} = \eta^{\text{dis,reg}}_{i^*} q^{\text{dis,reg}}_{i^*tw} - \frac{q^{\text{ch,reg}}_{i^*tw}}{\eta^{\text{ch,reg}}_{i^*}} \quad \forall t,w \tag{6.10c}$$

$$q^{\text{dis,reg}}_{i^*tw} \leq \zeta^{\text{dis,reg}}_{i^*} Q^{\text{s,reg}}_{i^*} \quad \forall t,w \tag{6.10d}$$

$$q^{\text{ch,reg}}_{i^*tw} \leq \zeta^{\text{ch,reg}}_{i^*} Q^{\text{s,reg}}_{i^*} \quad \forall t,w \tag{6.10e}$$

$$0 \leq \sum_{k=1}^{t} \left(q^{\text{ch,reg}}_{i^*kw} - q^{\text{dis,reg}}_{i^*kw}\right)\Delta \leq Q^{\text{s,reg}}_{i^*} \quad \forall t,w \tag{6.10f}$$

$$P_{i^*tw}\left(.\right) \leq P^{\text{cap}} \quad \forall t,w \tag{6.10g}$$

where $q^{\text{ig,reg}}_{i^*tw}$ (decision variable) is the wind (intermittent) generation level of the regulated firm in node i^* at time t under scenario w, $Q^{\text{ig,reg}}_{i^*}$ is its maximum wind generation capacity, and $c^{\text{ig,reg}}_{i^*}$ is its marginal cost of wind generation. Moreover, $q^{\text{ch,reg}}_{i^*tw}$,$q^{\text{dis,reg}}_{i^*tw}$ (decision variables), and $q^{\text{s,reg}}_{i^*tw}$ (intermediate decision variable) are the charge, discharge and net charge/discharge levels of the regulated firm in node i^* at time t under scenario w, respectively. The constraint (6.10b) is similar to the constraint in the wind generation problem (6.6b), and the constraints (6.10c)-(6.10f) are similar to the constraints in the storage arbitrage problem (6.8b)-(6.8e). The reason why maximizing the $\frac{P_{i^*tw}(.)}{-\beta_{i^*t}} - c^{\text{ig,reg}}_{i^*} q^{\text{ig,reg}}_{i^*tw} - c^{\text{s,reg}}_{i^*}\left(q^{\text{dis,reg}}_{i^*tw} + q^{\text{ch,reg}}_{i^*tw}\right)$ is equivalent to maximizing the social welfare for the regulated wind-storage firm in our problem is based on the discussion in Appendix B on regulated firms.

6.3 Solution Approach

Here, the bi-level storage and wind allocation problem reducing the average price and price volatility is transformed into a single-level Mathematical Problem with Equilibrium Constraints (MPEC). The equivalent single-level (MPEC) problem is solved by a uniform line search algorithm, which is different from our methodology for solving the single-level problem in Chapter 5.

6.3.1 Solution Method for the lower level problem

The regulated wind and storage capacities are the only variables that couple the scenarios in the lower level problem. Therefore, for any regulated wind and storage capacity amounts, each scenario of the lower level problem can be solved autonomously and the market equilibrium can be obtained by solving the KKT conditions of all firms. The existence of the Bayes-NE solution at the lower level problem is stated in Proposition 6.1.

Proposition 6.1. *For any vector of regulated wind and storage capacity amounts,* $[Q_{i^*}^{\text{ig,reg}}, Q_{i^*}^{\text{s,reg}}]$*, the lower level game admits a Bayes-NE.*

Proof: The objective function of any firm in the game is continuous and quasi-concave in its strategy, and their strategy space is non-empty, compact and convex. Therefore, according to Theorem 1.2 in [79], the lower level game admits a Bayes-NE. ■

In the lower level problem, the nodal market prices depend on the regulated wind and storage capacities through the constraints (6.10b) and (6.10d-6.10f). This dependency allows us to minimize the objective function on the upper level problem using the optimal values of regulated wind and storage capacities.

6.3.2 Solution Method for the equivalent single level problem

Imposing the KKT conditions of all firms as constraints in the optimization problem (6.3), we can transform our bi-level problem into the following single-level optimization problem:

$$\min\,(1-k)\sqrt{\mathsf{Var}\left(\{P_{i^*tw}\}_{tw}\right)}+k\overline{\mathsf{E}}\left(\{P_{i^*tw}\}_{tw}\right) \tag{6.11a}$$

s.t.

$$(6.3b) \tag{6.11b}$$

$$\text{KKT}\,(6.6a-6.6c) \tag{6.11c}$$

$$\text{KKT}\,(6.8a-6.8f) \tag{6.11d}$$

$$\text{KKT}\,(6.7a-6.7f) \tag{6.11e}$$

$$\text{KKT}\,(6.9a-6.9d) \tag{6.11f}$$

$$\text{KKT}\,(6.10a-6.10g) \tag{6.11g}$$

where the optimization variables are the regulated wind and storage capacities, the bidding strategies of all firms, and the set of all Lagrangian multipliers. Note that the feasible region is not necessarily convex or even connected because of the nonlinear complementary constraints. It is possible to write the equivalent single level problem (6.11) as a Mixed-Integer Non-Linear Problem (MINLP), but the large number of integer variables makes the problem computationally infeasible.

Considering the equality constraint (6.3b), there is just one decision variable on the upper level problem. We perform a uniform line search on the variable $Q_{i^*}^{\text{ig,reg}}$, i.e., the single decision variable of the upper level problem, with N iterations. We increase the regulated wind capacity by $\Delta Q^{\text{ig,reg}}$ and decrease the regulated storage capacity by $\Delta Q^{\text{s,reg}}$, which is a function of $\Delta Q^{\text{ig,reg}}$, and find the Bayes-NE solution of the lower level game at each iteration. Comparing the average price and price volatility calculated at different iterations, we find the optimal regulated wind and storage allocation, as described in Algorithm 2.

6.4 Case Study and Simulation Results

In this section, we apply our bi-level price management framework to Australia's National Electricity Market (NEM). The inverse demand functions in our model are cal-

Algorithm 2 The line search (N-step) algorithm for finding the wind-storage allocation.

$\Delta Q^{\text{ig,reg}} = \frac{B}{NI^{\text{ig}}}$
initial point $\leftarrow Q^{\text{ig,reg}} = 0,\ Q^{\text{s,reg}} = \frac{\text{B}}{I^{\text{s}}}$
for iteration = 0 : N **do**
  iteration=iteration+1
  $Q_{i^*}^{\text{ig,reg}}(\text{iteration}) \leftarrow Q_{i^*}^{\text{ig,reg}}(\text{iteration}-1) + \Delta Q^{\text{ig,reg}}$
  $Q_{i^*}^{\text{s,reg}} \leftarrow \frac{\text{B}-I^{\text{ig}}Q_{i^*}^{\text{ig,reg}}}{I^{\text{s}}}$
  $\boldsymbol{q}^{\star}(\text{iteration}) \leftarrow$ Lower level problem Bayes–NE
  $\overline{\mathsf{E}}(\text{iteration}), \overline{\mathsf{Var}}(\text{iteration}) \leftarrow (6.1b, 6.1a)$ at Bayes–NE
end for
$Q_{i^*}^{\text{ig,reg}*} \leftarrow \underset{Q_{i^*}^{\text{ig,reg}}}{\text{find}}\left(\min\left((1-k)\sqrt{\overline{\mathsf{Var}}\left(Q_{i^*}^{\text{ig,reg}}\right)} + k\overline{\mathsf{E}}\left(Q_{i^*}^{\text{ig,reg}}\right)\right)\right)$
$Q_{i^*}^{\text{s,reg}*} \leftarrow \frac{\text{B}-I^{\text{ig}}Q_{i^*}^{\text{ig,reg}*}}{I^{\text{s}}}$

ibrated with historical demand and price data from the year 2016. Different types of electricity generation firms, such as coal, gas, hydro, biomass, and wind, with total generation capacity of 46 GW were active in NEM in 2016 [12]. In our numerical study, we consider 365 scenarios each representing a 24-hour wind power availability and electricity demand profiles. The realistic data in different regions of NEM from the year 2016 is used to generate the scenario set (Source of data: AEMO). Note that all the prices are in Australian dollar.

6.4.1 Impact of Generation Capacity, Gas Price and Transmission Line on Average Price and Price Volatility in NEM

In this subsection, we first study the average price and price volatility in the NEM by considering two cases. In our primary case, the NEM market is simulated based on the available data in 2016. In our secondary case, the Hazelwood coal power plant in VIC is closed down, the gas price in total NEM is increased, and the Basslink transmission line, between VIC and TAS, which was under maintenance in 2016, is restarted in comparison to the primary case. Table 6.1 compares the simulated wholesale electricity prices in five regions of NEM in the primary and secondary cases. Our simulation results show that the average price of electricity increases in all regions, about 14.27% in NEM, due to Hazelwood power plant closure and gas price surge. The highest rate of price increment belongs to VIC, about 40.33%, where the coal plant was located, following by its neighboring region SA with 19.80%. According to our numerical results, restarting the Basslink interconnector between VIC and TAS reduces the impacts of coal plant closure and gas price surge on the electricity price in TAS, which increases just by 3.58% in average.

Table 6.1: Wholesale electricity prices ($/MWh) in five-node NEM market in primary and secondary cases.

	SA	QLD	TAS	**VIC**	NSW	NEM
Primary Case	108.97	72.32	99.64	**57.48**	58.81	67.27
Secondary Case	130.55	78.94	103.20	**80.66**	61.65	76.87
Change%	19.80	9.16	3.58	**40.33**	4.83%	14.27

Our calculation also shows that price volatility increases in NEM after the coal plant closure and gas price surge. The square root of price volatility increases by 17.7% in NEM, where VIC experiences the highest increase rate of 41.5%. The Basslink transmission line also suppresses the price volatility in TAS due to the Hazelwood closure and gas price surge.

6.4.2 Managing the Average Price and Price Volatility by Only Regulated Wind or Only Regulated Storage

In this subsection, we study the impact of installing only regulated wind or only regulated storage on the average price and price volatility in VIC, where the coal power plant is closed down. We start our simulations with the equivalent annual budget of 300 m$, and perform the sensitivity analysis with other amounts of the equivalent annual budget, between zero and 300 m$, later. Considering the investment cost of 2400 $/kW and lifespan of 25 years, the equivalent annual cost is 96 $/(kW.yr) for wind generation. Also, with the investment cost of 600 $/kWh and lifespan of 10 years, the equivalent annual cost is 60 $/(kWh.yr) for battery storage. Therefore, the equivalent annual budget of 300 m$ is almost equivalent to 5000 MWh battery capacity or 3125 MW wind capacity.

Fig. 6.1 shows the impact of installing only 5000 MWh regulated battery on the wholesale electricity prices in VIC. According to this figure, the regulated battery in VIC charges at off-peak times and discharges at peak hours, i.e., makes profit from electricity arbitrage. The charge/discharge of the installed battery approximately results in the average peak price reduction of 47 $/MWh and the average off-peak price increment of 16 $/MWh in VIC. The average wholesale electricity price in VIC decreases from 80.6 $/MWh to 72.9 $/MWh due to the addition of 5000 MWh regulated battery.

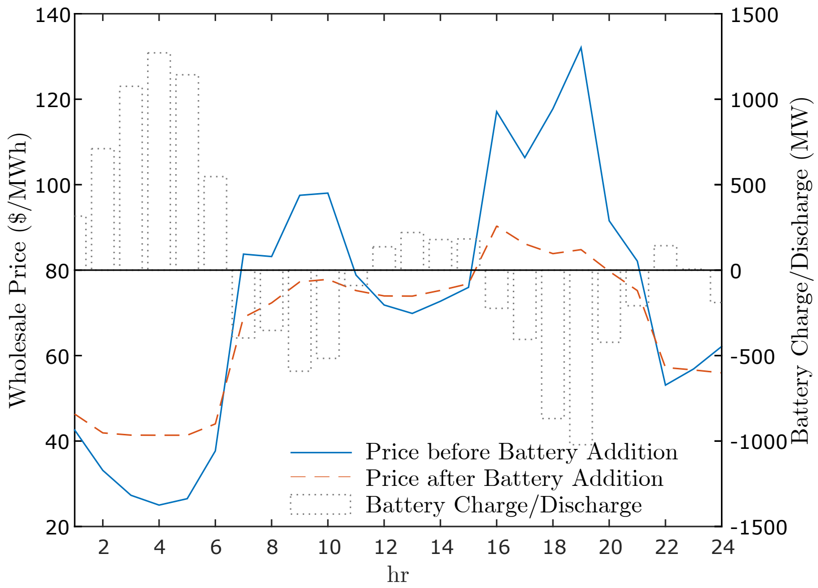

Figure 6.1: Mean (over 365 scenarios) wholesale electricity prices in VIC before and after addition of only 5000 MWh regulated battery storage capacity.

Fig. 6.2 shows the impact of installing only 3125 MW regulated wind on the wholesale electricity prices in VIC. The regulated wind in our model with capacity of 3125 MW generates electricity with average level of 975 MW, i.e., with capacity factor of 31%, in VIC. The generation of the regulated wind firm results in the average peak and off-peak wholesale price reductions of 28 $/MWh and 5 $/MWh, respectively, in VIC. The average wholesale electricity price in VIC decreases from 80.6 $/MWh to 62 $/MWh due to the 3125 MW wind capacity addition. This observation confirms that wind power generators are more efficient in average price reduction than storage firms.

Fig. 6.3a and 6.3b compare the impact of a regulated wind with that of a regulated storage on the average price and the price volatility, respectively, in VIC when the equivalent annual budget increases from zero to 300 m$. It can be seen that for different levels of budget, i.e., different levels of capacity, the regulated storage is more efficient in reducing the price volatility whereas the regulated wind is more efficient in reducing the

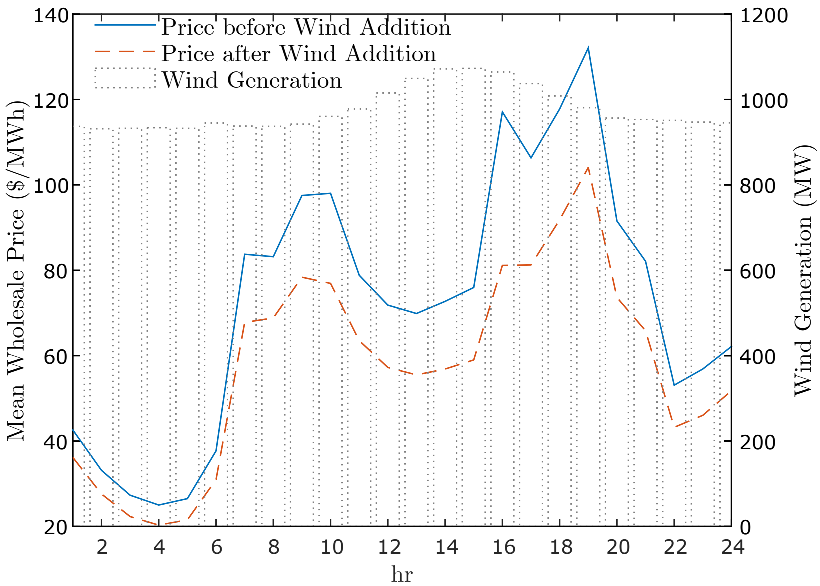

Figure 6.2: Mean (over 365 scenarios) wholesale electricity prices in VIC before and after addition of only 3125 MW regulated wind generation capacity.

average price. Given the equivalent annual budget of 300 m$, the regulated storage and the regulated wind reduce the square root of price volatility in VIC by 71.14 % and 53.55 %, respectively. However, with the same equivalent annual budget, regularized storage and wind firms reduce the average price in VIC by 10.04 % and 29.08 %, respectively. This observation shows the effectiveness of storage in price volatility reduction and wind in average price reduction.

Moreover, in addition to mean price and price volatility reduction impacts, the cost analysis of the regulated wind and regulated storage can affect the investment decisions. Fig. 6.3c indicates the cost analysis of the regulated wind and regulated storage in VIC when the equivalent annual budget varies from zero to 300 m$. The life time rate of return less than 100 % shows a financially unprofitable investment. Based on this figure, the regulated wind is financially profitable in VIC when the equivalent annual investment cost is less than 300 m$, but the regulated storage makes profit in VIC when the equivalent annual investment cost is less than 100 m$. Note that future reduction in battery cost makes the large investments on batteries profitable.

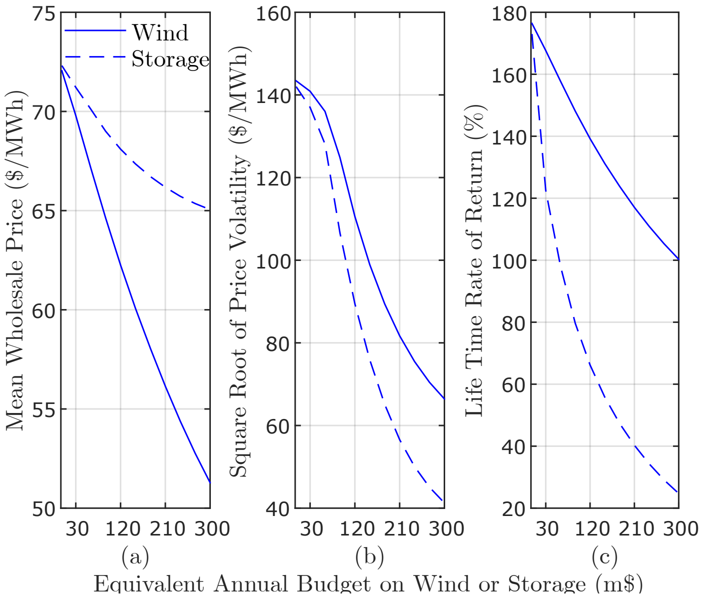

Figure 6.3: The mean price, the square root of price volatility, and the life time rate of return for only regulated wind and only regulated battery allocation versus the equivalent annual budget in VIC.

6.4.3 Managing the Average Price and Price Volatility by Mixture of Regulated Wind and Storage in VIC

In this subsection, we study the impact of jointly optimal regulated wind and storage allocation on the mean price and price volatility. Fig. 6.4 illustrates the normalized mean wholesale price as well as the normalized square roof of price volatility for different mixtures of wind and battery allocation with the equivalent annual budget of 300 m$ in VIC. The mean wholesale prices are normalized with base value of 73 $/MWh, which is the average price in the market before adding regulated wind-storage capacities, and the square root of price volatilities are normalized with the base value of 143 $/MWh, which is the square root of price volatility in the market before adding regulated wind-storage capacities. According to Fig. 6.4, the increase of the regulated wind share, ξ, (or equivalently, the decrease of regulated storage share, 1-ξ) results in lower average prices but higher price volatility levels in the market, and vice versa. Therefore, depending on the importance of average price or price volatility, i.e., the coefficient k, the total budget can be allocated on a mixture of regulated wind and battery capacities.

Fig. 6.5 shows the budget allocation share between regulated wind (ξ) and regulated

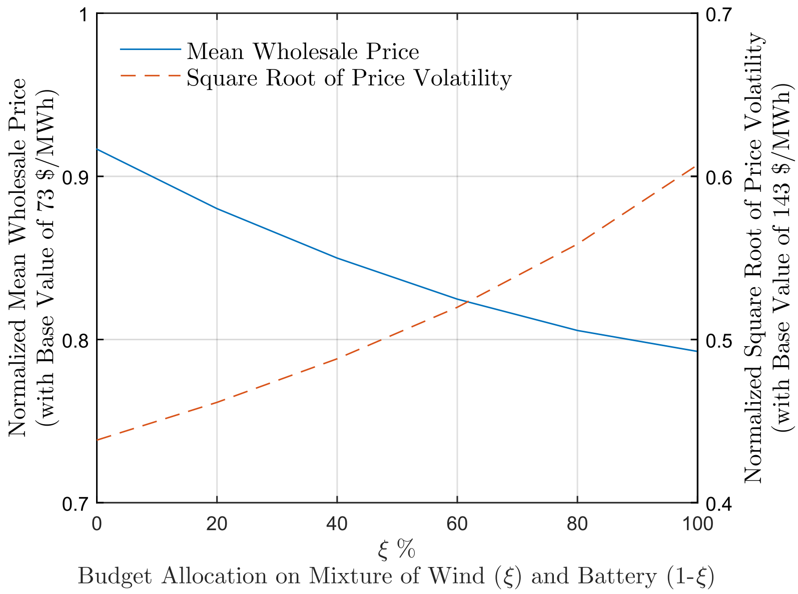

Figure 6.4: Normalized mean wholesale price and square root of price volatility for different mixtures of regulated wind and regulated battery with the equivalent annual budget of 300 m$ in VIC.

battery $(1 - \xi)$ when the weighting coefficient of price volatility and average price in the upper level problem (6.3), k, varies from zero to one. The logistic shape of the optimal budget share function with respect to the weighting coefficient k verifies our observations regarding the impacts of wind and storage firms on the price. The optimal share of regulated wind is more than that of the regulated storage when average price reduction is prioritized, i.e., when $0.5 \leq k \leq 1$. Similarly, when price volatility reduction is more important, i.e., when $0 \leq k \leq 0.5$, the optimal share of regulated battery is more than that of the regulated wind. The decision making on the budget share is highly sensitive with respect to parameter k when the average price and the price volatility are almost equally important, i.e., $0.4 \leq k \leq 0.6$.

6.5 Conclusion

Closure of base-load coal power plants, and gas price surge may increase the average price and price volatility in electricity markets. Our study presents an optimization framework which allocates a budget on regulated wind and storage capacities in order

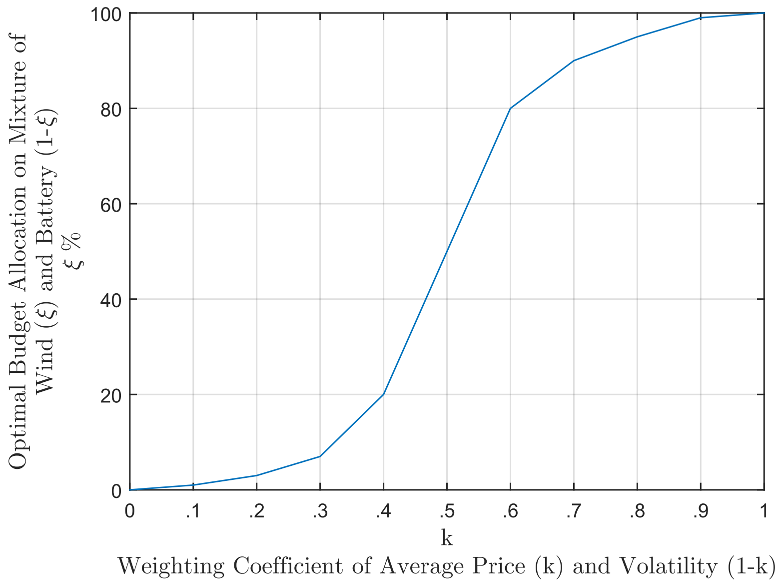

Figure 6.5: The budget allocation share between the regulated wind and the regulated battery as a function of the weighting factor k with the equivalent annual budget of 300 m$ in VIC.

to minimize the weighted sum of the average price and the price volatility. Based on our numerical results in NEM, the impacts of regulated wind and storage on average price and price volatility can be summarized as:

- In a multi-region electricity market, closure of a coal power plant in one region may affect the electricity prices in other regions. After the closure of Hazelwood power plant in VIC, the average price and volatility increased in VIC and its neighboring regions, but not in TAS. Reopening the Basslink interconnector between VIC and TAS in 2017 prevented to observe significant price increase in TAS despite the Hazelwood closure and gas price surge.

- Both storage and wind affect the average price and price volatility in electricity markets. Storage technologies can reduce the price and the price volatility by electricity price arbitrage. Being spread across the network, wind turbines can also decrease the price and volatility in electricity markets. However, storage is more efficient in price volatility reduction than wind whereas wind is more efficient in average price reduction.

- Although disptchable generators are more efficient in reducing the price volatility, wind turbines, if being spread across the network, can also reduce the price volatility level in the market. In our model, a single node represents an entire state, and hence, incorporates diversity of wind generation across a large geographic region that counteracts natural intermittency of wind generation.
- Based on the importance of average price and price volatility, a mix capacity of regulated wind and storage can be allocated in a region to reach the desired level of price and volatility in the market.
- Wind turbine, with small or large capacity, is already a competent technology which is able to recover its life time cost in the market, but storage technology is economical just in small to medium size, e.g., battery capacity larger than 1300 MWh in VIC is not economically profitable. Future reduction of technology costs can make it economical to install larger batteries in the market.
- Our developed model is generalized to consider any type of storage technology. However, in our case study, we studied the battery storage, which is likely to penetrate in large scale in Australia's electricity market in future.

The operation of generators, storage utilities and the transmission lines are the decision variables in our developed operational wholesale electricity market models. In Chapters 7 and 8, we develop long term electricity market models, which include operation and investment decision variables, and use them to design long-term emission abatement and fast response capacity support policies in the market.

Part III

Designing Incentive Policies in Electricity Markets

Introduction to Part III

IN THIS Part, we develop long-term planning Cournot-based electricity market models, which are used to design incentive policies on reducing the emission and maintaining the system reliability in the network. The designed policies are in forms of tax and subsidy.

In Chapter 7, a generation expansion electricity market model, including strategic and regulated generation firms, is developed. All players in the game maximize their utilities subject to a emission cap constraint, the dual variable of which is used to design the emission tax required to achieve the emission reduction target in the market.

In Chapter 8, an electricity market evolution model, including strategic and regulated generation, storage and transmission firms, is developed. Any player in the game maximizes its utility subject to an emission intensity reduction constraint and a fast response dispatchable generation constraint. The dual variable of the emission constraint is used to design the tax/subsidy incentives required to achieve the emission intensity target and the dual variable of the fast response constraint is used to design the tax/subsidy incentives required to achieve the reliability (balance between demand and supply) target in the market.

Chapter 7

Long-Term Stochastic Planning in Electricity Markets with a Carbon Cap Constraint

Carbon price in an electricity market provides incentives for carbon emission abatement and renewable generation technologies. Policies constraining or penalizing carbon emission can significantly impact the capacity planning decisions of both fossil-fueled and renewable generators. Uncertainties due to intermittency of various renewable generators can also affect the carbon emission policies. This chapter proposes a Cournot-based long-term capacity expansion model taking into account a carbon cap constraint for a partly concentrated electricity market dealing with stochastic renewables using a Bayesian game. The stochastic game is formulated as a centralized convex optimization problem and solved to obtain a Bayes-Nash Equilibrium (Bayes-NE) point. The stochastic nature of a generic electricity market is illustrated with a set of scenarios for wind availability, in which three generation firms (coal, gas, and wind) decide on their generation and long-term capacity investment strategies. Carbon price is derived as the dual variable of the carbon cap constraint. Embedding the carbon cap constraint in the game leads to more investment on renewable generators and less on fossil-fueled power plants. However, higher levels of intermittency from renewable generation leads to higher carbon prices required to meet the carbon cap constraint in the market. This paves the way towards storage technologies and diversification of distributed generation as means to encounter intermittency in renewable generation.

7.1 Introduction

IN THIS chapter, we theoretically develop a stochastic game-theoretic Cournot-based model which calculates a Bayes-NE point in partly concentrated electricity markets, having both strategic and perfectly competitive (fringe) generation players. In addition to generation portfolio, the firms decide on expanding their capacities during the study period dealing with the uncertainties due to intermittency of certain renewables, e.g., stochasticity of wind and solar. Players decide on new capacity investment and their generation by considering a set of scenarios for wind and solar availability and a carbon cap constraint during the study period. The dual variable of the carbon cap constraint is used to calculate the the carbon price required to meet the targeted carbon emission cap in the market. The stochastic nature of our model enables us to find the effect of intermittent renewables on the carbon price.

Moreover, capacity retirement and remaining value of new generation capacities are considered in our model. It means that power plants become retired once time passes their plant life and the remaining value of each new invested technology at the end of the study period is subtracted from its investment cost. For instance, a generator having $\mathbf{T}'$ years plant life pays just $\frac{1}{\mathbf{T}'}$ of the investment cost in our model if it decides to install a new capacity exactly at the last year in our model. However, the annualized investment cost ($/MW/yr) is an alternative way instead of considering the remaining values of new invested technologies, e.g. in [32]; although it is not hard to construct an unusual example where this is not true.

The **contributions** of this chapter include the following:

- A long-term stochastic generation capacity expansion model with an emission cap constraint is developed which captures the strategic behavior of generation firms. A set of scenarios is included in the model due to the intermittency of wind and solar energies.

- The carbon price required to restrict the emission in the market, which is due to the greenhouse gas control or green network policies, is calculated based on the dual variable of the emission cap constraint at the Bayes-NE point of the game.

- The structure of our long-term model enables us to find the intertemporal expansion and retirement of the generation capacities and the remaining value of new generation capacities in the market.

The rest of this chapter presents the wholesale electricity market model with strategic and perfectly competitive generation players in Section 7.2, illustrative results in Section 7.3, and ends with a discussion and conclusion in Section 7.4.

7.2 Game-Theoretic Formulation of Long-term Wholesale Electricity Market

In a Cournot-Nash wholesale electricity market model, the generation players (firms) make their decisions strategically in order to maximize their utility functions, and the equilibrium price is equal to the inverse demand function. However, participants in a partly concentrated liberalized electricity market are either strategic or perfectly competitive. The strategic players decide on their generation to set the price in the market as price maker players, i.e., they hold market power, while the perfectly competitive players either are not large enough to affect the price (fringe participants) or are regulated to not benefit from their market power.

At the same time, the intermittent wind and solar powers are stochastic, which brings a great deal of uncertainty to the market. Decisions on new capacities have to be made considering a set of scenarios for wind and solar availabilities during the study period taking also into account a carbon emission cap constraint. Accordingly, we define the following extended Cournot-based Bayesian game model to find the long-term equilibrium point of the market.

7.2.1 Game Definition and Bayes-Nash Equilibrium

In the well-known Cournot electricity market model, several strategic generation companies make their generation decisions non-cooperatively given that the price follows the inverse demand function. However, we study a partly concentrated market in which there is perfectly competitive generation companies besides the oligopoly generators.

In a Bayesian game, players maximize their expected utility over alternative possibilities with a known probability distribution [81]. Availability of the stochastic renewables is captured in our model in a set of scenarios with given probabilities, consistent with the Bayesian game definition.

Definition 2. *A perfectly competitive (PC) player does not have the market power to raise the wholesale price, where a strategic player may deliberately withholds its available capacity to increase the price.*

Let $k \in \mathcal{K} = \{1, ..., K\}$ be in the set of generation firms (generators) participating in the electricity market, $y \in \mathcal{Y} = \{1, ..., Y\}$ be in the set of times with length of ΔY_y (yr), $s \in \mathcal{S} = \{1, ..., S\}$ be in the set of load zones (like seasons in a year) with length of ΔS_s $(\frac{\text{day}}{\text{yr}})$, $t \in \mathcal{T} = \{1, ..., T\}$ be in the set of sub-load zones (like off-peak, shoulder and peak times in a day) with length of ΔT_t $(\frac{\text{hr}}{\text{day}})$, and $w \in \mathcal{W}$ be in the set of scenarios on wind availability in our Bayesian game. Total duration of sub-load zone t that repeats on load zone s from period y is $\Delta l_{yst} = \Delta Y_y \Delta S_s \Delta T_t$ hours.

In our game $\mathcal{G}$, firm k decides on its generation q_{kystw} $(\forall y, s, t, w)$ and new capacities Q^{new}_{ky} $(\forall y)$ in order to maximize its utility U_k. We assume that the generator k has constant marginal cost of production (\$/MWh), $c_k \geq 0$, constant capacity maintenance cost (\$/MW/yr), $m_k \geq 0$, and constant investment cost (\$/MW), $Inv_k \geq 0$.

Definition 3. *A non-cooperative Bayesian game among $\mathcal{K} = \{1, ..., K\}$ players having the decision variables $q = [q_1, ..., q_K]$ and $Q^{new} = [Q^{new}_1, ..., Q^{new}_K]$ that aim to maximize their expected profit U over scenarios $w \in \mathcal{W}$ with probabilities Ψ_w is defined as $\mathcal{G} = \{\mathcal{K}, (q, Q^{new}) \succeq 0, U\}$.*

In a Cournot-based electricity market model, such as [7], the commonly-used linear price P follows the inverse demand function with intercept of α and slope of β:

$$P_{ystw} = \alpha_{yst} - \beta_{yst} D_{ystw} \quad \forall y, s, t, w \tag{7.1}$$

where D_{ystw} is the total electricity demand at time (y, s, t) and under scenario w.

Players in the market are categorized into two groups:

- perfectly competitive ($\gamma_k = 1$): which could be a set of fringe participants or a regulated competitive firm.
- strategic ($\gamma_k = 0$) or Cournot players.

Player k calculates its best responses, i.e., $q_k^* = \{q_{kystw}^*\}_{y,s,t,w}$, $Q_k^{\text{new}*} = \{Q_{ky}^{\text{new}*}\}_y$, by solving the following utility maximization problem:

$$\max_{\substack{q_k, Q_k^{\text{new}} \\ Q_k^{\text{total}}, D \succeq 0}} U_k : \sum_y \frac{1}{(1+r)^y} \left(\sum_{w,s,t} \Psi_w \Delta l_{yst} \left((\alpha_{yst} - \beta_{yst} D_{ystw}) q_{kystw} + \gamma_k \frac{\beta_{yst}}{2} q_{kystw}^2 - c_k q_{kystw} \right) \right.$$
$$\left. - m_k \Delta Y_y Q_{ky}^{\text{total}} - Inv_k Q_{ky}^{\text{new}} \right) + \frac{1}{(1+r)^Y} \max(0, \frac{PL_k + y - Y - 1}{PL_k}) Inv_k Q_{ky}^{\text{new}} \quad (7.2)$$

$s.t.$

$$D_{ystw} = \sum_k q_{kystw} \qquad \forall y, s, t, w \qquad (7.3)$$

$$q_{kystw} \leq Q_{ky}^{\text{total}} \qquad \forall y, s, t, w \qquad (7.4)$$

$$Q_{ky}^{\text{total}} = \sum_{y'=max(1,y-PL_k+1)}^{y} Q_{ky'}^{\text{new}} + \sum_{y''=Y_0-PL_k+y+1}^{Y_0} Q_{k,y''}^{\text{old}} \qquad \forall y \qquad (7.5)$$

$$q_{kystw} - q_{kys(t-1)w} \leq R_k^{\text{up}} Q_{ky}^{\text{total}} \qquad \forall y, s, t, w \qquad (7.6)$$

$$q_{kys(t-1)w} - q_{kystw} \leq R_k^{\text{dn}} Q_{ky}^{\text{total}} \qquad \forall y, s, t, w \qquad (7.7)$$

$$q_{kystw} \leq \omega_{kystw} Q_{ky}^{\text{total}} \qquad \forall y, s, t, w \qquad (7.8)$$

$$\sum_{s,t} q_{kystw} \leq RA_{ky} \qquad \forall y, w \qquad (7.9)$$

where q_k, Q_k^{new} are independent variables and Q_k^{total}, D are intermediate variables.

For strategic player k, the objective function (7.2) sums the expectation of revenue, $q_{kystw}(\alpha_{yst} - \beta_{yst} D_{ystw})$, minus the operation cost, $c_k q_{kystw}$, with probabilities of Ψ_w over scenarios $w \in \mathcal{W}$, the maintenance cost, $m_k Q_{ky}^{\text{total}}$, and the investment cost on the new capacity, $Inv_k Q_{ky}^{\text{new}}$, excluding its remaining value at the end time, $\max(0, \frac{PL_k+y-Y-1}{PL_k}) Inv_k Q_{ky}^{\text{new}}$. The revenues and costs over periods $\mathcal{Y}$ are discounted with respect to a specific base year Y_0 assuming discount rate $r(\%/\Delta Y_y)$. However, for a perfectly competitive player, the objective function has additional term $\frac{\beta_{yst}}{2} q_{kystw}^2$, which is equivalent to the market surplus loss when the player k is not perfectly competitive.

The supply/demand balance equation (7.3) equalizes the net consumption with the total generation. Capacity constraint (7.4) binds generation to its total capacity. Equality

(7.5) (This is the modified version of capacity constraint in [93]) sums the new capacities $Q^{\text{new}}_{ky'}$ and historical ones $Q^{\text{old}}_{k,y''}$ which are not retired at time y as the total capacity Q^{total}_{ky}. Constraints (7.6) and (7.7) consider the ramping up and down limits of the generator. The period-by-period power availability limit, applicable to all generators especially intermittent wind turbines, is shown in (7.8). Lastly, constraint (7.9) considers the inter-temporal generation limits due to planned/forced outages or fuel scarcity.

7.2.2 Carbon Price Calculation as a Dual Variable

Due to local and global concerns on greenhouse gases, there are upper bound restrictions on carbon emission in electricity generation. When fossil-fueled generators burn coal, natural gas or petroleum to produce electricity, they emit CO_2 gas as a side product. Considering the policy of pollution generation control in the market, we can calculate the desired carbon price required to achieve the upper bound on carbon emission constraint:

$$\sum_{k,s,t,w} \Psi_w \Delta l_{yst} EF_k q_{kystw} \leq E^{CO_2}_y (1-\phi) \quad : \quad \mu_y \quad \forall y \tag{7.10}$$

where $E^{CO_2}_y$ is the upper limit of CO_2 (tonne) emission in electricity industry during time y, and EF_k is the CO_2 emission coefficient of generator k (tonneCO_2/MWh). The dual variable of constraint (7.10), μ_y, is proportional to the target carbon price (\$/tonneCO_2) at time y that policy makers must announce to control the carbon pollution in the market. Note that the dual variable of the carbon cap constraint must be consistent in all individual profit maximization problems of all players in the NE point. Considering the first order optimality conditions of all individual problems (Karush-Kuhn-Tucker conditions), it can be shown that the variable $(1+r)^y EF_k \mu_y$ is the pollution tax that generator k pays during time y per each unit of electricity generation q_{kystw}.

7.2.3 Solving the Game as a Centralized Optimization Problem

The Bayes-NE point of the game including both strategic and perfectly competitive players at generation level, with the objective functions and constraints explained in Section

(7.2.1), can be computed by solving the following centralized optimization problem:

$$\max_{\substack{q,Q^{\text{new}}\\Q^{\text{total}},D\geq 0}} \sum_{y} \frac{1}{(1+r)^{y}} \Bigg(\sum_{s,t,w} \Psi_{w} \Delta l_{yst} \bigg((\alpha_{yst} - \frac{\beta_{yst}}{2} D_{ystw}) D_{ystw} - \sum_{k} \frac{\beta_{yst}}{2} (1-\gamma_{k}) {q_{kystw}}^{2} + c_{k} q_{kystw} \bigg)$$

$$- \sum_{k} m_{k} \Delta Y_{y} Q^{\text{total}}_{ky} + Inv_{k} Q^{\text{new}}_{ky} \Bigg) + \frac{1}{(1+r)^{Y}} \sum_{k} \max(0, \frac{PL_{k} + y - Y - 1}{PL_{k}}) Inv_{k} Q^{\text{new}}_{ky} \quad (7.11)$$

$s.t.$

$(7.3) - (7.10) \quad \forall k$

where q, Q^{new} are independent variables and Q^{total}, D are intermediate variables.

The objective function (7.11) sums the total surpluses of demand and supply in the market minus the market surplus loss regarding the suppliers' strategic behaviors. The centralized optimization problem is subjected to the constraints of all individual players' profit maximization problems.

In this chapter, the centralized quadratic optimization problem is solved to find the Bayes-NE point of the game. However, it is possible to write the KKT conditions of individual profit maximization problems and solve it as a Linear Complementarity Problem in distributed fashion.

7.3 Numerical Analysis

For illustrative purposes, we numerically investigate a generic single-node system comprising three generation firms- coal, gas, and wind- planning for capacity installation during next 25 years, including 5 time steps (ΔY_{y}=5 years), consisting of peak (ΔT_{peak}=4 hours a day), shoulder ($\Delta T_{\text{shoulder}}$=10 hours a day) and off-peak ($\Delta T_{\text{off-peak}}$=10 hours a day) load zones for a whole year (ΔS=365 days in a year). The parameters for the inverse demand function (7.1) are listed in Table 7.1, which indicate the highest values for α and the lowest values for β at peak load zones. Assuming electricity demand increases over years, the parameter α is raised with rate of 5% every 5 years.

Considering investment, maintenance, operation and fuel costs in addition to life time of technologies and their ramping up and down specifications, which are listed in Table

Table 7.1: The parameters for the inverse demand function.

	y, $\Delta y = 5$ years	1	2	3	4	5
	peak	240	252	264	277	291
$\alpha_{y,t}$	shoulder	200	210	220	231	243
	off-peak	160	168	176	185	194
	peak	.08	.08	.08	.08	.08
$\beta_{y,t}$	shoulder	.1	.1	.1	.1	.1
	off-peak	.12	.12	.12	.12	.12

7.2 [94], the generation firms decide on participating in the market. The parameter γ is zero for coal and gas-fueled generators, which shows they play strategically, and is one for the wind firm, which means that it plays perfectly competitively.

Table 7.2: Costs and technology specifications of generation firms.

firms	Investment ($/kW)	Maintenance ($/kW/yr)	Operation & Fuel ($/kWh)	Plant Life (5years)	RampUp & Dn
coal	2500	25	0.015	8	0
gas	1000	10	0.055	6	0.9
wind	3000	30	0	4	1

The base values for wind power availability is assumed 40% at off-peak times, 30% at shoulder times, and 10% at peak times. In wind availability scenarios, wind power availability is assumed to vary σ% above and under its base values as shown in Figure 7.1.

Employing the commercial solver CONOPT in GAMS software [95], the centralized quadratic optimization problem is solved with the mentioned input data to calculate the Bayes-NE point of the game.

7.3.1 Impact of Carbon Cap on Capacity Planning

Total carbon production of the system without any pollution control policy is calculated in our model based on the emission factors of 0.93 tonne_{CO_2}/MWh for coal and .55 tonne_{CO_2}/MWh for gas as listed in Table 7.3.

The simulation is repeated for two different values of carbon reduction percentage $\phi \in \{20, 40\%\}$ and is compared with no carbon cap scenario in Figure 7.2. Total car-

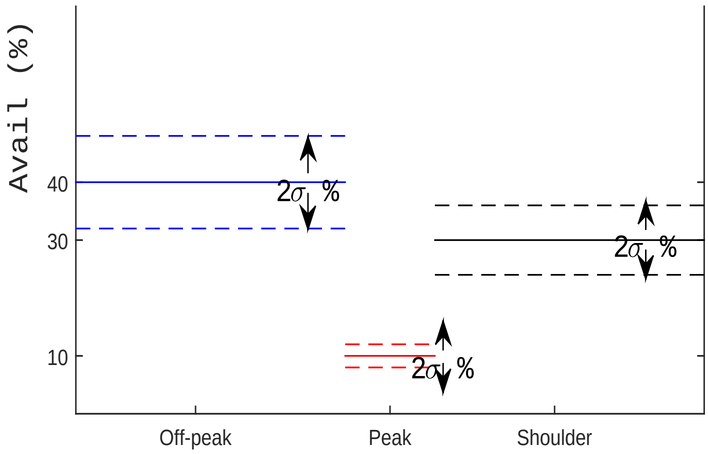

Figure 7.1: Normalized wind capacity availability (ω_t) during off-peak, shoulder, and peak load zones, distributed on [(1-σ)$E(\omega)$, (1+σ)$E(\omega)$] with the given expected value $E(\omega)$.

Table 7.3: Total CO_2 emission every five years in the system with no carbon cap constraint.

y (5-years)	1	2	3	4	5
$E_y^{CO_2}$ (million_tonne)	31.8	33.0	34.3	35.6	37.0

bon emission in the system becomes restricted, using the constraint (7.10) in the game model. Restricting the total carbon emission in the system leads to more investment on renewables and less on fossil-fueled power plants, especially coal-fueled generators. The price increase motivates renewables to invest more in our game model with carbon cap constraint.

7.3.2 Impact of Wind Stochasticity on Carbon Price

The dual variable of the carbon cap constraint at the Bayes-NE point is used to calculate the carbon price. Policy makers can announce the carbon price as a tax to make the power plants comply with the pollution policies in the market. Stochasticity arising from intermittent generators impacts the values of carbon price. Figure 7.3 represents the calculated carbon price at every five-year period respectively for $\phi \in \{20\%, 60\%\}$ carbon emission reduction policies in two scenarios of deterministic ($\sigma = 0$) and stochastic

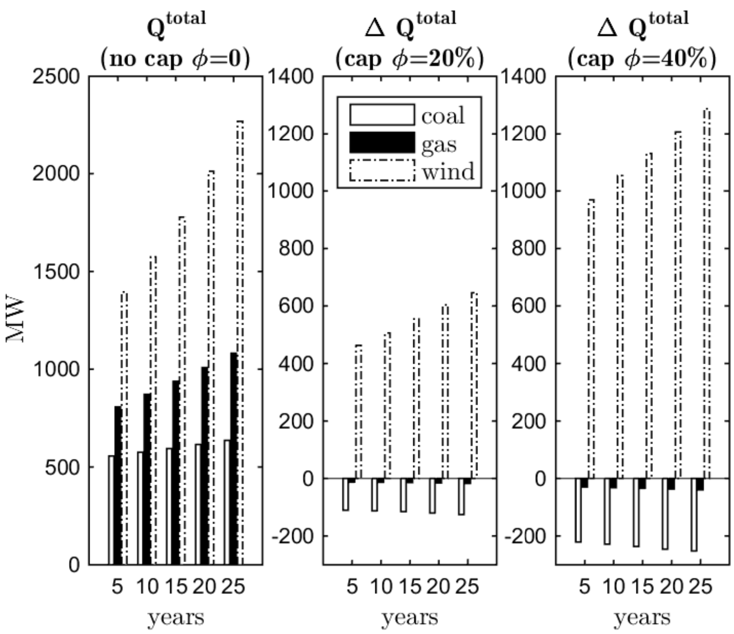

Figure 7.2: Capacity investment Q^{total} and its change ΔQ^{total} due to carbon cap constraint with coefficient $\phi \in \{20, 40\%\}$.

($\sigma = 60\%$) wind power availability. Simulation results show that higher carbon prices are calculated when stricter emission reduction is targeted in the market, and also higher carbon prices are required to meet the carbon cap constraint when the intermittentcy from renewable generators is higher in the market.

7.3.3 Impact of Wind Player's Strategic Behavior on Capacity Planning

We compare the capacity planning of all generators when wind firm participating in the market is strategic or perfectly competitive. The wind player representing all wind turbines in our model is a profit maximizer player in the strategic wind case and a fringe player in the perfectly competitive wind case. It is observed that proportionally the coal firm installs more generation capacity, the gas firm slightly lowers its capacity expansion rate, and the wind player installs much less new generation capacity in the strategic wind case compared to the perfectly competitive wind case, as is shown in Figure 7.4.

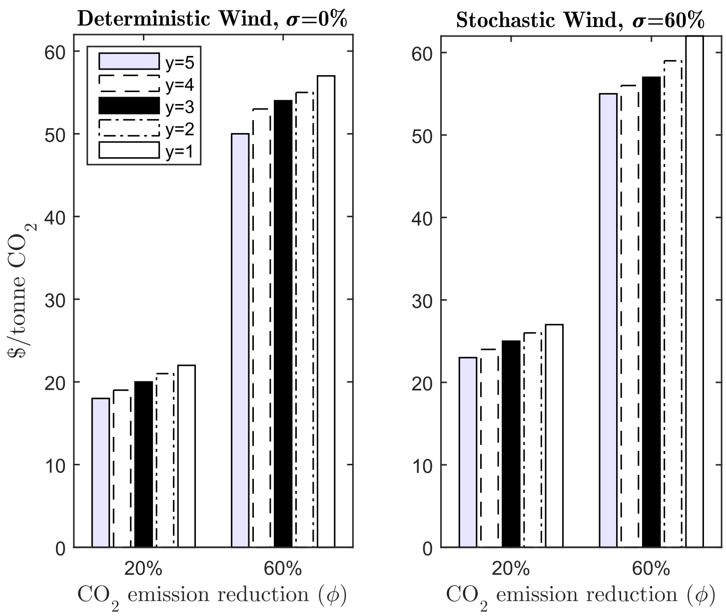

Figure 7.3: Carbon pricing for different CO_2 emission reduction scenarios ($\phi \in \{20\ \%, 60\ \%\}$).

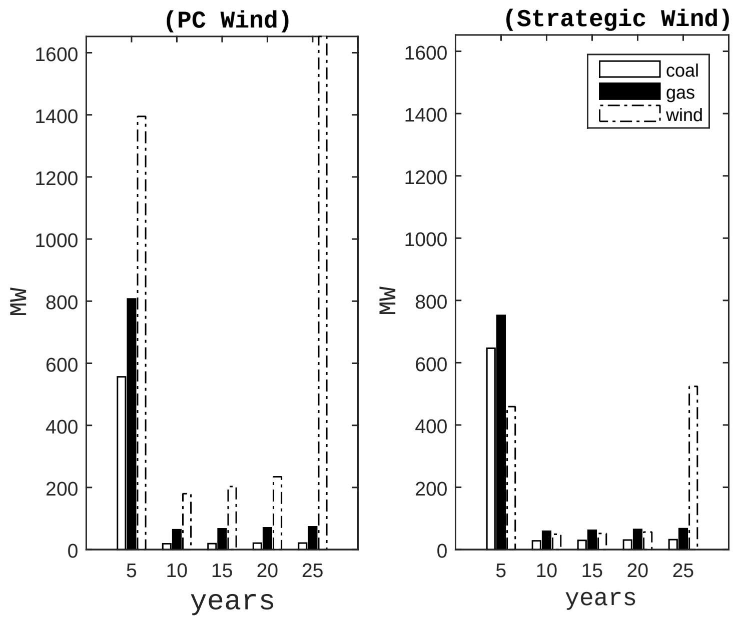

Figure 7.4: New capacity installation Q^{new} considering wind strategy (perfectly competitive and strategic).

7.3.4 Impact of Remaining Value on Capacity Planning

In our simulations, we assume that there is no existing generation capacity (incumbent capacity) in the network. The generation firms consider the remaining value of new capacities when they make their generation expansion decisions. Figure 7.5 indicates that ignoring the remaining values biases the new capacity installation decisions. In fact, it leads to more new capacity installation in the earlier periods so that generation firms being able to recover their costs on new capacities. The reason is that without considering the remaining values a firm cannot return its investment cost during the study period if it decides to add installations at the ending periods.

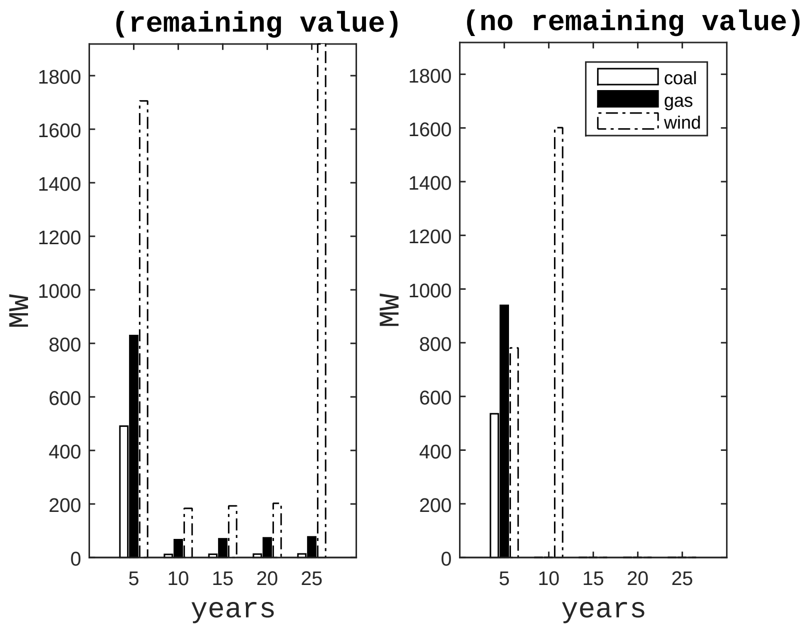

Figure 7.5: New capacity installation considering remaining value.

Considering the remaining values, the coal firm and the gas firm install most of their new capacities in the first period, but the wind firm renews its capacity in the fifth period as its technology retires after four periods. Further technological maturity of renewable technologies, i.e., achieving longer plant life, would lessen their annualized investment cost and increase their competitiveness in the market.

7.4 Conclusion

New capacity expansion is dependent on the market price expectation, which is highly affected by renewable energies availability. Moreover, policy makers can intervene in the market via setting tax on carbon emission to meet their goals. The modeling analysis presented in this chapter studies the impacts of carbon cap constraint on long-term capacity investment decisions of generation firms facing stochastic renewable power availability. Based on our model and the simulation results, the impacts of carbon cap on capacity expansion of three coal, gas and wind generation firms are as following:

- Carbon cap constraint in the game model results in proportionally more new renewable and less fossil-fueled generation capacity, especially less coal-fueled capacity.
- Dual variable of the carbon cap constraint at the Bayes-NE point is used to calculate the carbon price in our model. Policy makers can announce it in the market as carbon emission tax, which leads to invest more on renewable capacities.
- Higher levels of intermittency from renewables makes them financially less attractive. Higher tax on carbon emission can make renewables able to compete with fossil-fueled generators even if renewables are highly intermittent. The difference in the carbon price can be used towards storage technologies and diversification of distributed generation as means to encounter intermittency in renewable generation.
- We intend to extend our stochastic game model to study the long term investment on storage technologies and transmission lines in addition to generation technologies. In the future, storage technologies, similar to renewables, are expected to achieve longer plant life and experience high capacity expansion due to reduction in their annualized investment costs.
- The input data in our model and simulations is consistent with the real data in Australias electricity market, and we can accept the conclusions in this chapter for the electricity markets which are similar to NEM.

By considering a carbon cap constraint in our developed long-term electricity market model, we designed the carbon tax amounts required to achieve the carbon abatement policies in the market. In Chapter 8, we design tax/subsidy policies required to achieve emission intensity reduction and fast response capacity support policies in the market by extending our long-term electricity market model.

Chapter 8

Designing Tax&Subsidy Incentives Towards a Green and Reliable Electricity Market

Incentive schemes and policies play an important role in reducing carbon emissions from electricity generation. This chapter investigates tax and subsidy incentives towards a reliable and low emission electricity market, using Australia's National Electricity Market (NEM) as a case study. A game-theoretical Cournot-based electricity market expansion model is developed, which calculates the capacity investment and retirement of any strategic/regulated generation, storage, and transmission player for multi investment periods, taking into account Emission Intensity Reduction and Fast Response Dispatchable Capacity constraints. Based on the dual variables of the emission reduction and the fast response generation constraints at the Nash Equilibrium solution of the game, the incentive policies (tax/subsidy) on emission and fast response capacity are designed, respectively. The simulation results for Australia's NEM during 2017-2052, indicates how large investment on thermal solar technology, battery storage and transmission lines supports high level of Variable Renewable Energy, wind and solar, penetration in a green and reliable electricity market. Improvement of new technologies and their cost reduction trajectory show that NEM does not need any emission incentive policy for up to 45% emission intensity reduction by 2052. However, higher emission reduction targets require imposing taxes on pollutant generators and subsidizing clean generators.

8.1 Introduction

IN THIS chapter, a strategically competitive electricity market expansion model, which includes the emission intensity reduction and fast response dispatchable capacity constraints, is proposed. The Nash Equilibrium (NE) solution of our model is used to design the incentive policies on emission reduction and fast response dispatchable capacity support. The dual variable of the emission constraint at the Nash Equilibrium solution of the game is used to design the emission incentive policies and the dual variable of the fast response dispatchable capacity constraint at the NE point is used to design the capacity incentive policies. In other words, the model is developed to illustrate the pathway towards a reliable and low emission future.

The contributions of this chapter are summarized as follows:

- A game-theoretical Cournot-based electricity market expansion model is proposed, which solves an unified operation and installation problem, to find the future capacity mix of generation, storage and transmission players in the market. All players in our model can be either strategic or perfectly competitive.

- Using the dual variable of the emission intensity reduction constraint at the NE point of our model, we calculate the emission tax and subsidy that generators are required to pay and receive for a targeted low emission market.

- Using the dual variable of the fast response generation constraint at the NE point of our model, we calculate the capacity tax and subsidy that generators and storage firms are required to pay and receive in order to maintain the system reliable.

Under the proposed framework, an electricity generation mix for Australia's NEM is designed such that the emission intensity target is achieved and the reliability is maintained. The incentive policies on emission and fast response capacity are also calculated using the NE solution of the game.

The rest of this chapter is organized as follows. The strategically competitive electricity market expansion model is formulated in Section 8.2. The equilibrium analysis of the problem and the solution method are presented in Section 8.3. The simulation results are presented in Section 8.4. The conclusion remarks are discussed in Section 8.5.

8.2 Strategically Competitive Electricity Market Expansion Model

In this section, we develop an electricity market expansion model which consists of generation, storage and transmission firms trading electricity in a multi-node energy-only wholesale electricity market. Let $\mathcal{N}_i^{\text{ig}}$ be the set of intermittent generators, such as wind/PV farms and roof-top PVs, located in node i, $\mathcal{N}_i^{\text{sg}}$ be the set of synchronous generators, such as coal, gas, hydro and thermal solar power plants, located in node i, $\mathcal{N}_i^{\text{st}}$ be the set of storage firms, such as pump-hydros and batteries (cooperatively controlled or non-cooperative), located in node i, and $\mathcal{N}_i^{\text{tr}}$ be the set of transmission lines connected to node i.

The market expansion problem is formulated as a Cournot-based game among the generation, storage and transmission players, which are introduced in detail in Section 8.2.4. At the NE solution of the game, the capacity investment strategies of the firms, their biding strategies as well as the equilibrium nodal prices are calculated. The market expansion game is solved under the emission intensity and fast response generation constraints, which their dual variables are used to calculate the tax and subsidy incentives.

8.2.1 Inverse Demand Functions

In our model, the electricity price in node i at investment period y, with duration of five years, and load time t, with duration of one hour, is given by the following, commonly-used linear inverse demand function:

$$P_{iyt}\left(D_{iyt}\right) = \alpha_{iyt} - \beta_{iyt} D_{iyt}, \tag{8.1}$$

$$D_{iyt} = \sum_{m \in \mathcal{N}_i^{\text{ig}}} q_{miyt}^{\text{ig}} + \sum_{n \in \mathcal{N}_i^{\text{sg}}} q_{niyt}^{\text{sg}} + \sum_{b \in \mathcal{N}_i^{\text{st}}} q_{biyt}^{\text{st}} + \sum_{j \in \mathcal{N}_i^{\text{tr}}} \left(\eta_{ij}^{\text{tr}} q_{ijyt}^{\text{tr}} - q_{jiyt}^{\text{tr}}\right) \ \forall i, y, t \tag{8.2}$$

where α_{iyt} and β_{iyt} are positive real values for the inverse demand function in node i at period y, and load time t. Besides, q_{miyt}^{ig} is the electricity generation of intermittent generator m in region i , q^{sg}_{niyt} is the electricity generation of synchronous generator n in region i, q^{st}_{biyt} is the electricity flow from storage firm b in node i, and q^{tr}_{ijyt} is the electricity flow from node j to node i at period y, and load time t. Note that the total amount of power supply from the generation, storage and transmission firms in node i is equal to the nodal net electricity demand, which represents the nodal electricity balance in our work.

Although roof-top PVs and residential batteries do not participate in the wholesale market, their operation affects the market price, i.e., shifts the inverse demand function up or down. Thus, instead of modeling the roof-top PVs and residential batteries on the demand side, we equivalently model them on the supply side as perfectly competitive players.

8.2.2 Total Capacity and Investment Functions

In our model, any player can retrofit its capacity at any investment period y. The total capacity of each firm at period y, Q_y, is the sum of incumbent (old) capacities, Q^{old}_y, which are given as exogenous input to the model, and new capacities, Q^{new}_y, which are decision variables of players, as:

$$Q_y(Q^{\text{new}}_{y' \le y}) = \sum_{y'=\max(1, y-PL+1)}^{y} Q^{\text{new}}_{y'} + \sum_{y''=Y_0-PL+y+1}^{Y_0} Q^{\text{old}}_{y''} \tag{8.3}$$

where PL denotes the plant life of the corresponding technology of the firm, and Y_0 is the base year in our study. Note that firms in our model are able to decommission their capacities at any period before they reach their plant life and each technology must become retired in our model when it reaches its plant life.

Market expansion models which assume annualized investment cost for technologies do not take capacity retirement into account [32]. Instead of using the annualized investment cost, we consider the whole technology costs and deduct the end of period remaining value of new capacities [33] from their investment costs in our model as:

$$Inv_y = \left(1 - \frac{\max(0, PL + y - N_Y - 1)}{PL}\right) \tilde{Inv} \tag{8.4}$$

where $\tilde{Inv}$ is the actual investment cost of a unit and Inv_y is the modified value of investment cost at period y in our model. For instance, in a 25-year period simulation study, $N_Y = 25$, if a firm with the technology plant life of 20 years decides to install a new unit at year 21, it just pays $\frac{1}{4}$ of the actual investment cost in our model. Note that we include the yearly maintenance costs of technologies as part of their investment costs and do not consider them separately.

8.2.3 The Emission and Capacity Incentive Policies

An upper bound on the emission intensity is considered in our model to ensure the emission intensity reduction in the market as:

$$\frac{\sum_{i,t} \sum_{n \in \mathcal{N}_i^{sg}} q^{sg}_{niyt} EF_{ni}}{\sum_{i,t} \sum_{n \in \mathcal{N}_i^{sg}} q^{sg}_{niyt} + \sum_{m \in \mathcal{N}_i^{ig}} q^{ig}_{miyt}} \leq \left(1 - \alpha^{ER}_y\right) EI^{CO_2}_{Y_0} : \mu^{ER}_y \ \forall y \tag{8.5}$$

where $EI^{CO_2}_{Y_0}$ is the CO_2 emission intensity of the whole electricity sector at base (reference) year Y_0, α^{ER}_y is the desired percentage of emission intensity reduction at period y relative to the base period Y_0, EF_{ni} is the emission factor of fossil-fueled synchronous generator n in node i. The dual variable associated with this constraint, i.e., μ^{ER}_y, corresponds to the required emission tax/subsidy (first incentive policy) to achieve a level of emission intensity, as shown in Section 8.3.3.

The second incentive policy is calculated based on the fast response dispatchable capacity constraint. The constraint limits the total VRE generation to a proportion of fast response generation during each investment period to ensure adequacy of fast response capacity in the network as:

$$\sum_t \left(\sum_{n \in \mathcal{N}_i^{\text{sg}}} \alpha_{ni}^{\text{sg,FR}} q_{niyt}^{\text{sg}} + \sum_{b \in \mathcal{N}_i^{\text{st}}} \alpha_{bi}^{\text{st,FR}} q_{biyt}^{\text{dis}} \right) \geq \alpha^{\text{FR}} \sum_t \sum_{m \in \mathcal{N}_i^{\text{ig}}} q_{miyt}^{\text{ig}} \; : \; \mu_{iy}^{\text{FR}} \;\; \forall i, y \tag{8.6}$$

where α^{FR} is the fast response proportion coefficient, $\alpha_{ni}^{\text{sg,FR}}$ is a binary coefficient which is one if firm n in region i is a fast response synchronous generator, such as gas-fired or hydro, $\alpha_{bi}^{\text{st,FR}}$ is a binary coefficient which is one if firm b in region i is a pump-hydro or a cooperatively controlled battery, and q_{biyt}^{dis} is the electricity discharge level of the storage firm b in node i. It is also shown in Section 8.3.3 that the required annual capacity subsidy/tax to ensure that there is enough fast response capacity in the network is calculated based on the dual variable of the fast response constraint, μ_{iy}^{FR}:

Note that we can reduce the coefficient α^{FR}, i.e., the need for fast response capacity to achieve diversity dividends, by spreading the wind and solar generation across the network, which smooths the generation and ramping up and down of the total regional intermittent electricity generation [96].

8.2.4 The Market Expansion Game

In this subsection, we introduce the market expansion game, the utility function of players and their decision variables. In our model, each firm decides on its expansion capacity and bidding strategies over the planning horizon, being either strategic or regulated.

Definition 8.1. *A strategic (price maker) firm sets its strategies over the time horizon maximizing its aggregate expected profit, but a regulated (price taker) firm aims to maximize the social welfare [77].*

In what follows, the variable μ indicates the associated Lagrange or dual variable of its corresponding constraint, the price function $P_{iyt}(.)$ refers to (8.1) and the total capacity function $Q(.)$ refers to (8.3).

Intermittent Generation Firms

The mth intermittent generator, i.e., wind or solar farm or roof-top PVs, in node i maximizes its profit by solving the following optimization problem:

$$\max_{\substack{\{q^{\text{ig}}_{miyt}\}_{yt} \\ \{Q^{\text{ig,new}}_{miy}\}_{y}}\succeq 0} \Delta l \sum_{y,t} \frac{P_{iyt}\,(.)\, q^{\text{ig}}_{miyt} - \left(c^{\text{ig}}_{mi} q^{\text{ig}}_{miyt} + \frac{d^{\text{ig}}_{mi}}{2} {q^{\text{ig}}_{miyt}}^2\right) + \gamma^{\text{ig}}_{mi} \frac{\beta_{iyt} {q^{\text{ig}}_{miyt}}^2}{2}}{(1+r)^y} - \sum_{y} \frac{Inv^{\text{ig}}_{miy} Q^{\text{ig,new}}_{miy}}{(1+r)^y} \tag{8.7a}$$

s.t.

$$q^{\text{ig}}_{miyt} \leq A^{ig}_{mit} Q^{\text{ig}}_{miy}(.) \;:\; \mu^{\text{ig}}_{miyt} \quad \forall y, t \tag{8.7b}$$

$$Q^{\text{ig}}_{miy}(.) \leq \bar{C}^{\text{ig}}_{mi} \;:\; \mu^{\text{ig},\bar{C}}_{miy} \quad \forall y, t \tag{8.7c}$$

$$(8.5), (8.6) \tag{8.7d}$$

where $Q^{\text{ig,new}}_{miy}$ and $Q^{\text{ig}}_{miy}(.)$ are the new capacity (variable) and the total generation capacity (function) of the intermittent (VRE) firm m in node i at period y, respectively. The first term in the summation in (8.7a) is the net present value of electricity generation revenue, the second term represents the generation cost, which is quadratic (with coefficients c^{ig}_{mi} and d^{ig}_{mi}) and reflects that cheaper renewable energy sites are deployed first, the third term denotes the regulation surplus when γ^{ig}_{mi} is one, given the discount rate r over the periods $y \in \{1, ..., N_Y\}$. The last term in (8.7a) is the total investment cost of new capacities, with unitary investment cost of Inv^{ig}_{miy}, over the periods. Depending on the binary parameter γ^{ig}_{mi}, the mth intermittent generation firm in node i behaves strategically or in a regulated manner. The firm acts strategically when γ^{ig}_{mi} is zero or acts as a regulated firm when γ^{ig}_{mi} is one. Considering the $\frac{\beta_{iyt} {q^{\text{ig}}_{miyt}}^2}{2}$ in the objective function, the firm becomes regulated (price taker), which helps to increase the competition and consequently the social welfare in the market. The constraint (8.7b) considers the regional intermittent energy availability coefficient in load time t, A^{ig}_{mit}, and the constraint (8.7c) limits the electricity generation to the maximum potential capacity, $\bar{C}^{\text{ig}}_{mi}$, e.g., the roof-top PV installation area limit.

Synchronous Generation Firms

The strategy of the nth synchronous generator, i.e., coal, gas, biomass, hydro or thermal solar firms, in node i is obtained by solving the following optimization problem:

$$\max_{\substack{\left\{q^{sg}_{niyt}\right\}_{yt} \succeq 0 \\ \left\{Q^{sg,new}_{niy}\right\}_{y}}} \quad \Delta l \sum_{y,t} \frac{P_{iyt}(.)\, q^{sg}_{niyt} - c^{sg}_{ni} q^{sg}_{niyt} + \gamma^{sg}_{ni} \frac{\beta_{iyt} {q^{sg}_{niyt}}^2}{2}}{(1+r)^y} - \sum_{y} \frac{Inv^{sg}_{niy} Q^{sg,new}_{niy}}{(1+r)^y} \tag{8.8a}$$

s.t.

$$q^{sg}_{niyt} \leq A^{sg}_{ni} Q^{sg}_{niy}(.) \;:\; \mu^{sg}_{niyt} \quad \forall y,t \tag{8.8b}$$

$$q^{sg}_{niyt} - q^{sg}_{niy(t-1)} \leq R^{up}_{ni} A^{sg}_{ni} Q^{sg}_{niy}(.) : \mu^{sg,up}_{niyt} \; \forall y,t \tag{8.8c}$$

$$q^{sg}_{niy(t-1)} - q^{sg}_{niyt} \leq R^{dn}_{ni} A^{sg}_{ni} Q^{sg}_{niy}(.) : \mu^{sg,dn}_{niyt} \; \forall y,t \tag{8.8d}$$

$$\sum_{t} q^{sg}_{niyt} \leq RA^{sg}_{niy} : \mu^{sg,RA}_{niy} \; \forall n,i,y \tag{8.8e}$$

$$(8.5), (8.6) \tag{8.8f}$$

where $Q^{sg,new}_{niy}$ and $Q^{sg}_{niy}(.)$ are the new capacity (variable) and total generation capacity (function) of the synchronous firm n in node i at period y. The parameter c^{sg}_{ni} represents the firm's marginal operation and fuel cost of electricity generation and the parameter Inv^{sg}_{niy} is its unitary investment cost. Depending on the binary parameter γ^{sg}_{ni}, the nth synchronous generator in node i acts strategically when γ^{sg}_{ni} is zero or acts as a regulated firm when γ^{sg}_{ni} is one. The constraint (8.8b) limits the electricity generation to its energy flow capacity with availability coefficient A^{sg}_{ni}. Constraints (8.8c) and (8.8d) ensure that the nth synchronous generator meets its ramping limits, with ramping up and down coefficients R^{up}_{ni} and R^{dn}_{ni}, and constraint (8.8e) limits the electricity generation during period y to energy availability limit RA^{sg}_{niy}, e.g. the dam water availability limit for hydros.

Storage Firms

The strategy of the bth storage firm, i.e., pump-hydro, or cooperatively controlled or non-cooperative batteries, in node i is obtained by solving the following optimization problem:

$$\max_{\substack{\left\{q^{\text{dis}}_{biyt}, q^{\text{ch}}_{biyt}\right\}_{yt} \succeq 0 \\ \left\{Q^{\text{st}^{\text{f}},\text{new}}_{biy}, Q^{\text{st}^{\text{v}},\text{new}}_{biy}\right\}_{y} \succeq 0 \\ \left\{q^{\text{st}}_{biyt}\right\}_{yt}}} \quad \Delta l \sum_{y,t} \frac{P_{iyt}\left(.\right) q^{\text{st}}_{biyt} + \gamma^{\text{st}}_{bi} \frac{\beta_{iyt} {q^{\text{st}}_{biyt}}^2}{2}}{(1+r)^y} - \sum_{y} \frac{Inv^{\text{st}^{\text{v}}}_{biy} Q^{\text{st}^{\text{v}},\text{new}}_{biy} + Inv^{\text{st}^{\text{f}}}_{biy} Q^{\text{st}^{\text{f}},\text{new}}_{biy}}{(1+r)^y} \tag{8.9a}$$

s.t.

$$q^{\text{st}}_{biyt} = \eta^{\text{dis}}_{bi} q^{\text{dis}}_{biyt} - \frac{q^{\text{ch}}_{biyt}}{\eta^{\text{ch}}_{bi}} \ : \ \mu^{\text{st}}_{biyt} \quad \forall y, t \tag{8.9b}$$

$$q^{\text{dis}}_{biyt} \leq A^{\text{st}}_{bi} Q^{\text{st}^{\text{f}}}_{biy}(.) \ : \ \mu^{\text{dis}}_{biyt} \quad \forall y, t \tag{8.9c}$$

$$q^{\text{ch}}_{biyt} \leq A^{\text{st}}_{bi} Q^{\text{st}^{\text{f}}}_{biy}(.) \ : \ \mu^{\text{ch}}_{biyt} \quad \forall y, t \tag{8.9d}$$

$$0 \leq \sum_{t'=1}^{t} \left(q^{\text{ch}}_{biyt'} - q^{\text{dis}}_{biyt'}\right) \Delta \leq A^{\text{st}}_{bi} Q^{\text{st}^{\text{v}}}_{biy}(.) : \mu^{\text{st,min}}_{biyt}, \mu^{\text{st,max}}_{biyt} \quad \forall y, t \tag{8.9e}$$

$$q^{\text{dis}}_{biyt} q^{\text{ch}}_{biyt} = 0 \ : \ \mu^{\text{dis/ch}}_{biyt} \quad \forall y, t \tag{8.9f}$$

(8.6) (8.9g)

where $Q^{\text{st}^{\text{v}},\text{new}}_{biy}$ and $Q^{\text{st}^{\text{f}},\text{new}}_{biy}$ are the new volume and flow capacity (variable), and $Q^{\text{st}^{\text{v}}}_{biy}(.)$ and $Q^{\text{st}^{\text{f}}}_{biy}(.)$ are the total volume and flow capacity (function) of the storage firm b in node i at period y, respectively. Note that the unit for volume capacity is MWh (energy) and for flow capacity is MW (power). The parameters $Inv^{\text{st}^{\text{v}}}_{biy}$ and $Inv^{\text{st}^{\text{f}}}_{biy}$ are the firm's unitary volume and flow investment costs, respectively. Depending on the binary parameter γ^{st}_{bi}, the bth storage firm in node i acts strategically when γ^{st}_{bi} is zero and acts as a regulated firm when γ^{st}_{bi} is one. The equality (8.9b) defines the net output/input flow of electricity, q^{st}_{biyt}, from/to storage firm b in node i. The constraints (8.9c) and (8.9d) limit the energy flow (discharge q^{dis}_{biyt} and charge q^{ch}_{biyt}) of the firm to its flow (discharge/charge) capacity with availability factor A^{st}_{bi}. Constraint (8.9e) ensures the volume capacity limit of the storage firm is always met. Finally, constraint (8.9f) prevents the storage firm charge and discharge simultaneously, which is the only non-linear constraint in our model.

Transmission Firms

The strategy of the transmission line between nodes i and j, which buys and sells electricity in regions it connects, is obtained by solving the following optimization problem:

$$\max_{\substack{\left\{q^{\text{tr}}_{jiyt}, q^{\text{tr}}_{ijyt}\right\}_{yt} \\ \left\{Q^{\text{tr,new}}_{ijy}, Q^{\text{tr,new}}_{jiy}\right\}_{y}} \succeq 0} \sum_{y,t} \Delta l \left(\frac{\left(\eta^{\text{tr}}_{ij} P_{jyt}(.) - P_{iyt}(.)\right) q^{\text{tr}}_{jiyt}}{(1+r)^y} + \frac{\left(\eta^{\text{tr}}_{ij} P_{iyt}(.) - P_{jyt}(.)\right) q^{\text{tr}}_{ijyt}}{(1+r)^y} + \right.$$
$$\left. \gamma^{\text{tr}}_{ij} \frac{\left(\eta^{\text{tr}\,2}_{ij} \beta_{iyt} + \beta_{jyt}\right) \frac{q^{\text{tr}\,2}_{ijyt}}{2} + \left(\eta^{\text{tr}\,2}_{ij} \beta_{jyt} + \beta_{iyt}\right) \frac{q^{\text{tr}\,2}_{jiyt}}{2} - \eta^{\text{tr}}_{ij} \left(\beta_{jyt} + \beta_{iyt}\right) q^{\text{tr}}_{ijyt} q^{\text{tr}}_{jiyt}}{(1+r)^y} \right) -$$
$$\sum_{y} \frac{\frac{Inv^{\text{tr}}_{ijy}}{2} \left(Q^{\text{tr,new}}_{ijy} + Q^{\text{tr,new}}_{jiy}\right)}{(1+r)^y} \tag{8.10a}$$

s.t.

$$q^{\text{tr}}_{ijyt} \leq A^{\text{tr}}_{ij} Q^{\text{tr}}_{ijy}(.) \;:\; \mu^{\text{tr}}_{ijyt} \quad \forall y, t \tag{8.10b}$$

$$Q^{\text{tr,new}}_{ijy} = Q^{\text{tr,new}}_{jiy} \;:\; \mu^{\text{tr,Q}}_{ijy} \quad \forall y \tag{8.10c}$$

where $Q^{\text{tr,new}}_{ijy}$ and $Q^{\text{tr}}_{ijy}(.)$ are the new capacity (variable) and the total transmission capacity (function) of the transmission firm between nodes i and j at period y. The first term in summation in (8.10a) is the electricity profit of transmitting electricity from node i to node j, the second term is the backward profit, the third term denotes the regulation surplus and the last term is the total investment cost of new capacities, with unitary investment cost of Inv^{tr}_{ijy}. Depending on the binary parameter γ^{tr}_{ij}, the transmission line between nodes i and j acts strategically when γ^{tr}_{ij} is zero or acts as a regulated firm when γ^{tr}_{ij} is one. Note that the electricity markets with regulated transmission lines are discussed as *electricity markets with transmission constraints* in the literature, e.g., [20, 35].

The constraint (8.10b) limits the electricity flow to the capacity of transmission lines with availability coefficient A^{tr}_{ij}, and the constraint (8.10b) ensures that transmission capacity on both directions of the line is equal in our model.

Note that the profit maximization problem (8.10a) looks more complex than our previous formulation in [52] because of considering the transmission efficiency, η^{tr}_{ij}, which was missing before.

8.3 Solution Methodology

In this section, we first provide a game-theoretic analysis of the market expansion game between generation, storage and transmission players. Next, we explain a method for solving the game based on a Mixed Complementarity Problem (MCP).

8.3.1 Game-theoretic Analysis of the Market Expansion Model

To solve the market expansion game, we need to study the best response functions of all firms participating in the market. Then, any intersection of all firms' best response functions will be a NE. At the NE strategy of the game, no player has any incentive to unilaterally deviate its strategy from the NE point.

Note that (8.9f), which is nonlinear, is the only constraint in our model that violates the sufficient conditions of Theorem 4.4 in [71] for existence of NE point. However, in our numerical results, we find the NE point of the game by varying the initial point of the optimization algorithm.

The orthogonal constraints corresponding to emission and fast response capacity with dual variables of μ^{ER}_{y} and μ^{FR}_{iy}, respectively, which exist in best response equation sets of all players, are given by:

$$\frac{\sum\limits_{i,t}\sum\limits_{n\in\mathcal{N}_i^{\text{sg}}} q^{\text{sg}}_{niyt} EF_{ni}}{\sum\limits_{i,t}\sum\limits_{n\in\mathcal{N}_i^{\text{sg}}} q^{\text{sg}}_{niyt} + \sum\limits_{m\in\mathcal{N}_i^{\text{ig}}} q^{\text{ig}}_{miyt}} \leq \left(1-\alpha^{\text{ER}}_{y}\right) EI^{\text{CO}_2}_{Y_0} \perp \mu^{\text{ER}}_{y} \geq 0 \tag{8.11a}$$

$$\sum_t \left(\sum_{n \in \mathcal{N}_i^{\text{sg}}} \alpha_{ni}^{\text{sg,FR}} q_{niyt}^{\text{sg}} + \sum_{b \in \mathcal{N}_i^{\text{st}}} \alpha_{bi}^{\text{st,FR}} q_{biyt}^{\text{dis}} \right) \geq \alpha^{\text{FR}} \sum_t \sum_{m \in \mathcal{N}_i^{\text{ig}}} q_{miyt}^{\text{ig}} \perp \mu_{iy}^{\text{FR}} \geq 0 \tag{8.11b}$$

Best Responses of Intermittent Generation Firms

The best response of the intermittent generator m in node i, given the strategies of other firms in the market, satisfies the necessary and sufficient Karush-Kuhn-Tucker (KKT) conditions ($t \in \{1, ..., N_T\}$; $y \in \{1, ..., N_Y\}$):

$$\Delta l \frac{P_{iyt}(.) - \left(c_{mi}^{\text{ig}} + d_{mi}^{\text{ig}} q_{miyt}^{\text{ig}}\right) - \beta_{iyt} q_{miyt}^{\text{ig}} \left(1 - \gamma_{mi}^{\text{ig}}\right)}{(1+r)^y} - \mu_{miyt}^{\text{ig}} + \left(1 - \alpha_y^{\text{ER}}\right) EI_{Y_0}^{\text{CO}_2} \mu_y^{\text{ER}} - \alpha^{\text{FR}} \mu_{iy}^{\text{FR}}$$
$$\leq 0 \perp q_{miyt}^{\text{ig}} \geq 0 \tag{8.12a}$$

$$\frac{-Inv_{miy}^{\text{ig}}}{(1+r)^y} - \sum_{y'=y}^{\min(N_Y, y+PL_{mi}^{\text{ig}}-1)} \left(\mu_{miy'}^{\text{ig},\bar{C}} - \sum_t A_{mit}^{\text{ig}} \mu_{miy't}^{\text{ig}} \right) \leq 0 \perp Q_{miy}^{\text{ig,new}} \geq 0 \tag{8.12b}$$

$$q_{miyt}^{\text{ig}} \leq A_{mit}^{\text{ig}} Q_{miy}^{\text{ig}}(.) \perp \mu_{miyt}^{\text{ig}} \geq 0 \tag{8.12c}$$

$$q_{miyt}^{\text{ig}} \leq \bar{C}_{mi}^{\text{ig}} \perp \mu_{miyt}^{\text{ig},\bar{C}} \tag{8.12d}$$

where the perpendicularity sign, $\perp$, indicates that one of the adjacent inequalities must at least be satisfied as an equality [73].

Best Responses of Synchronous Generation Firms

The best response of the synchronous generator n in node i, given the collection of strategies of other firms in the market, is obtained by solving the following KKT conditions ($t \in \{1, ..., N_T\}$; $y \in \{1, ..., N_Y\}$):

$$\Delta l \frac{P_{iyt}(.) - c_{ni}^{\text{sg}} - \beta_{iyt} q_{niyt}^{\text{sg}} \left(1 - \gamma_{ni}^{\text{sg}}\right)}{(1+r)^y} - \mu_{niyt}^{\text{sg}} + \mu_{niy(t+1)}^{\text{up}} - \mu_{niyt}^{\text{up}} - \mu_{niy(t+1)}^{\text{dn}} + \mu_{niyt}^{\text{dn}} - \mu_{niy}^{\text{sg,RA}}$$
$$- \left(EF_{ni} - \left(1 - \alpha_y^{\text{ER}}\right) EI_{Y_0}^{\text{CO}_2}\right) \mu_y^{\text{ER}} + \alpha_{ni}^{\text{sg,FR}} \mu_{iy}^{\text{FR}} \leq 0 \perp q_{niyt}^{\text{sg}} \geq 0 \tag{8.13a}$$

$$\frac{-Inv^{\text{sg}}_{niy}}{(1+r)^y} + \sum_t A^{\text{sg}}_{ni} \sum_{y'=y}^{\min(N_Y, y+PL^{\text{sg}}_{ni}-1)} (\mu^{\text{sg}}_{niy't} + R^{\text{up}}_{ni}\mu^{\text{up}}_{niy't} + R^{\text{dn}}_{ni}\mu^{\text{dn}}_{niy't}) \leq 0 \;\perp\; Q^{\text{sg,new}}_{niy} \geq 0 \tag{8.13b}$$

$$q^{\text{sg}}_{niyt} \leq A^{\text{sg}}_{ni} Q^{\text{sg}}_{niy}(.) \;\perp\; \mu^{\text{sg}}_{niyt} \geq 0 \tag{8.13c}$$

$$q^{\text{sg}}_{niyt} - q^{\text{sg}}_{niy(t-1)} \leq R^{\text{up}}_{ni} A^{\text{sg}}_{ni} Q^{\text{sg}}_{niy}(.) \;\perp\; \mu^{\text{up}}_{niyt} \geq 0 \tag{8.13d}$$

$$q^{\text{sg}}_{niy(t-1)} - q^{\text{sg}}_{niyt} \leq R^{\text{dn}}_{ni} A^{\text{sg}}_{ni} Q^{\text{sg}}_{niy}(.) \;\perp\; \mu^{\text{dn}}_{niyt} \geq 0 \tag{8.13e}$$

$$\sum_t q^{\text{sg}}_{niyt} \leq RA^{\text{sg}}_{niy} \;\perp\; \mu^{\text{sg,RA}}_{niy} \geq 0 \tag{8.13f}$$

Best Responses of Storage Firms

The best response of the storage firm b in node i, given the collection of strategies of other firms in the market, is obtained by solving the following KKT conditions ($t \in \{1, ..., N_T\}$; $y \in \{1, ..., N_Y\}$):

$$\Delta l \frac{P_{iyt}(.) - \beta_{iyt} q^{\text{st}}_{biyt} \left(1 - \gamma^{\text{st}}_{bi}\right)}{(1+r)^y} + \mu^{\text{st}}_{biyt} = 0 \tag{8.14a}$$

$$-\eta^{\text{dis}}_{bi}\mu^{\text{st}}_{biyt} - \mu^{\text{dis}}_{biyt} - \Delta \sum_{t'=t}^{N_T} \mu^{\text{st,min}}_{biyt'} - \mu^{\text{st,max}}_{biyt'} + \alpha^{\text{st,FR}}_{bi}\mu^{\text{FR}}_{iy} + \mu^{\text{dis/ch}}_{biyt} q^{\text{ch}}_{biyt} \leq 0 \perp q^{\text{dis}}_{biyt} \geq 0 \tag{8.14b}$$

$$\frac{\mu^{\text{st}}_{biyt}}{\eta^{\text{ch}}_{bi}} - \mu^{\text{ch}}_{biyt} + \Delta \sum_{t'=t}^{N_T} \mu^{\text{st,min}}_{biyt'} - \mu^{\text{st,max}}_{biyt'} + \mu^{\text{dis/ch}}_{biyt} q^{\text{dis}}_{biyt} \leq 0 \perp q^{\text{ch}}_{biyt} \geq 0 \tag{8.14c}$$

$$\frac{-Inv^{\text{st}^{\text{v}}}_{biy}}{(1+r)^y} + \sum_t A^{\text{st}}_{bi} \sum_{y'=y}^{\min(N_Y, y+PL^{\text{st}^{\text{v}}}_{bi}-1)} \mu^{\text{st,max}}_{biy't} \leq 0 \perp Q^{\text{st}^{\text{v}},\text{new}}_{biy} \geq 0 \tag{8.14d}$$

$$\frac{-Inv^{\text{st}^{\text{f}}}_{biy}}{(1+r)^y} + \sum_t A^{\text{st}}_{bi} \sum_{y'=y}^{\min(N_Y, y+PL^{\text{st}^{\text{f}}}_{bi}-1)} \mu^{\text{dis}}_{biy't} + \mu^{\text{ch}}_{biy't} \leq 0 \perp\; Q^{\text{st}^{\text{f}},\text{new}}_{biy} \geq 0 \tag{8.14e}$$

$$q^{\text{st}}_{biyt} = \eta^{\text{dis}}_{bi} q^{\text{dis}}_{biyt} - \frac{q^{\text{ch}}_{biyt}}{\eta^{\text{ch}}_{bi}} \tag{8.14f}$$

$$q^{\text{dis}}_{biyt} \leq A^{\text{st}}_{bi} Q^{\text{st}^{\text{f}}}_{biy}(.) \;\perp\; \mu^{\text{dis}}_{biyt} \geq 0 \tag{8.14g}$$

$$q^{\text{ch}}_{biyt} \leq A^{\text{st}}_{bi} Q^{\text{st}^{\text{f}}}_{biy}(.) \;\perp\; \mu^{\text{ch}}_{biyt} \geq 0 \tag{8.14h}$$

$$0 \leq \sum_{t'=1}^{t} \left(q^{\text{ch}}_{biyt'} - q^{\text{dis}}_{biyt'} \right) \Delta \ \perp \ \mu^{\text{st,min}}_{biyt} \geq 0 \tag{8.14i}$$

$$\sum_{t'=1}^{t} \left(q^{\text{ch}}_{biyt'} - q^{\text{dis}}_{biyt'} \right) \Delta \leq A^{\text{st}}_{bi} Q^{\text{st}^{\text{v}}}_{biy}(.) \perp \mu^{\text{st,max}}_{biyt} \geq 0 \tag{8.14j}$$

$$q^{\text{dis}}_{biyt} q^{\text{ch}}_{biyt} = 0 \tag{8.14k}$$

Best Responses of Transmission Firms

Finally, the best response of the transmission firm between nodes i and j, given the collection of strategies of other firms in the market, can be obtained using the KKT conditions ($t \in \{1, ..., N_T\}$; $y \in \{1, ..., N_Y\}$):

$$\Delta l \frac{\eta^{\text{tr}}_{ij} P_{iyt}(.) - P_{jyt}(.) + \left(1 - \gamma^{\text{tr}}_{ij}\right) \left(\left(-\beta_{iyt} \eta^{\text{tr}^2}_{ij} - \beta_{jyt} \right) q^{\text{tr}}_{ijyt} + \eta^{\text{tr}}_{ij} \left(\beta_{iyt} + \beta_{jyt} \right) q^{\text{tr}}_{jiyt} \right)}{(1+r)^y} - \mu^{\text{tr}}_{ijyt}$$
$$\leq 0 \ \perp \ q^{\text{tr}}_{ijyt} \geq 0 \tag{8.15a}$$

$$\frac{\frac{-Inv^{\text{tr}}_{ijy}}{2}}{(1+r)^y} + \mu^{\text{tr,Q}}_{ijy} - \mu^{\text{tr,Q}}_{jiy} + \sum_t A^{\text{tr}}_{ij} \sum_{y'=y}^{\min(N_Y, y+PL^{\text{tr}}_{ij}-1)} \mu^{\text{tr}}_{ijy't} \leq 0 \perp \ Q^{\text{tr,new}}_{ijy} \geq 0 \tag{8.15b}$$

$$q^{\text{tr}}_{ijyt} \leq A^{\text{tr}}_{ij} Q^{\text{tr}}_{ijy}(.) \ \perp \ \mu^{\text{tr}}_{ijyt} \geq 0 \tag{8.15c}$$

$$Q^{\text{tr,new}}_{ijy} = Q^{\text{tr,new}}_{jiy} \tag{8.15d}$$

8.3.2 The Mixed Complementarity Problem

The NE solution is by definition the intersection of best responses of all players. Therefore, it satisfies the KKT conditions of all market players, that is, (8.11a-8.11b), (8.12a-8.12d), (8.13a-8.13f), (8.14a-8.14k), and (8.15a-8.15d). Consequently, the NE solution is the result of the following Mixed Complementarity Problem (MCP):

$$(8.11a - 8.11b), (8.12a - 8.12d), (8.13a - 8.13f), (8.14a - 8.14k), (8.15a - 8.15d)$$
$$m \in \{1, ..., N^{\text{ig}}_i\}, n \in \{1, ..., N^{\text{sg}}_i\}, b \in \{1, ..., N^{\text{st}}_i\}, i, j \in \{1, ..., I\}, t \in \{1, ..., N_T\}, y \in \{1, ..., N_Y\}$$

where the decision variables are the bidding strategies of all players, and set of Lagrange multipliers or dual variables in KKT conditions. We used the PATH solver in GAMS software to solve the MCP problem.

8.3.3 Interpreting the Dual Variables as Tax and Subsidy

In this subsection, based on dual variable of the emission constraint (8.5), μ_y^{ER}, and dual variable of the fast response constraint (8.6), μ_{iy}^{FR}, at the NE point of the game, we calculate the CO_2 emission tax/subsidy and the economic value of fast response capacity, respectively, in our model.

Firstly, we explain the carbon taxing/subsidizing mechanism in our model. From equation (8.13a), it is observed that the term $\frac{(1+r)^y}{\Delta l}\left(EF_{ni} - \left(1-\alpha_y^{\text{ER}}\right) EI_{Y_0}^{CO_2}\right)\mu_y^{\text{ER}}$ constitutes a portion of the price function, $P_{iyt}\left(.\right)$, when q_{niyt}^{sg} is positive, which can be interpreted as the tax/subsidy the synchronous generator n in node i must pay/receive per each MWh electricity generation at period y. Similarly, it can be seen in equation (8.12a) that the term $\frac{(1+r)^y}{\Delta l}\left(1-\alpha_y^{\text{ER}}\right) EI_{Y_0}^{CO_2}\mu_y^{\text{ER}}$ is equal to the subsidy the intermittent renewable generator m in node i, which is wind or solar, receives per each MWh electricity generation at period y.

Secondly, we explain the fast response capacity mechanism in our mode. The term $\alpha^{\text{FR}}\mu_{iy}^{\text{FR}}$ in equation (8.12a), the term $\alpha_{ni}^{\text{sg,FR}}\mu_{iy}^{\text{FR}}$ in equation (8.13a), and the term $\alpha_{bi}^{\text{st,FR}}\mu_{iy}^{\text{FR}}$ in equation (8.14b) constitute a portion of the price function, $P_{iyt}\left(.\right)$, when q_{miyt}^{ig}, q_{niyt}^{sg} and q_{biyt}^{dis} are positive, respectively. Therefore, at the NE solution the term $\frac{\Delta l \sum_t \alpha^{\text{FR}}\mu_{iy}^{\text{FR}} q_{miyt}^{\text{ig}}}{Q_{miy}^{\text{ig}}(.)}$ is equal to the fast response capacity tax that in average one MW intermittent generator pays per each period y, and $\frac{\Delta l \sum_t \alpha_{ni}^{\text{sg,FR}}\mu_{iy}^{\text{FR}} q_{niyt}^{\text{sg}}}{Q_{niy}^{\text{sg}}(.)}$, and $\frac{\Delta l \sum_t \alpha_{bi}^{\text{st,FR}}\mu_{iy}^{\text{FR}} q_{biyt}^{\text{dis}}}{Q_{biy}^{\text{st,f}}(.)}$ are equal to the fast response capacity subsidy that in average one MW synchronous generator and one MW storage firm receives per each period y, respectively.

8.3.4 The Market Expansion Model in Practice

Based on the dual variables of the emission constraint (8.5) and the fast response constraint (8.6) at the NE point of the game, i.e., $\mu_y^{\text{ER}^*}$, and $\mu_{iy}^{\text{FR}^*}$, the market players solve the corresponding optimization problems with their new objective functions, disregarding the emission and fast response constraints. Therefore, in practice, the intermittent generator m in region i, disregarding the constraints (8.5), (8.6), equivalently solves its optimization problem (8.7) with the following additional term in its objective function:

$$+\sum_{y,t}\left(1-\alpha_y^{\mathrm{ER}}\right)EI_{\mathrm{Y}_0}^{\mathrm{CO_2}}\mu_y^{\mathrm{ER}^*}q_{miyt}^{\mathrm{ig}}-\sum_{y,t}\alpha^{\mathrm{FR}}\mu_{iy}^{\mathrm{FR}^*}q_{miyt}^{\mathrm{ig}},$$

the synchronous generator n in region i, disregarding the constraints (8.5), (8.6), equivalently solves its optimization problem (8.8) with the following additional term in its objective function:

$$-\sum_{y,t}\left(EF_{ni}-\left(1-\alpha_y^{\mathrm{ER}}\right)EI_{\mathrm{Y}_0}^{\mathrm{CO_2}}\right)\mu_y^{\mathrm{ER}^*}q_{niyt}^{\mathrm{sg}}+\sum_{y,t}\alpha_{ni}^{\mathrm{sg,FR}}\mu_{iy}^{\mathrm{FR}^*}q_{niyt}^{\mathrm{sg}},$$

the storage firm b in region i, disregarding the constraint (8.6), equivalently solves its optimization problem (8.9) with the following additional term in its objective function:

$$+\sum_{y,t}\alpha_{bi}^{\mathrm{st,FR}}\mu_{iy}^{\mathrm{FR}^*}q_{biyt}^{\mathrm{dis}},$$

and the transmission line between nodes i and j solves the same optimization problem (8.10). Note that the solution of the updated market expansion model with the tax and subsidy terms is exactly equal to the NE solution of the game.

Note that the market operator or a government entity solves our game model and calculates the equilibrium values of $\mu_y^{\mathrm{ER}^*}$, and $\mu_{iy}^{\mathrm{FR}^*}$. Any inaccurate information used in calculating the tax/subsidy amounts may lead to significant deviation from the desired emission and reliability levels in the market.

8.4 Case Study and Simulation Results

In this section, we apply our Market Expansion framework to the Australia's NEM. The investment is calculated every five years from 2017 to 2052 in our model, considering a representative (averaged) 24-hour operation time (load time) horizon. The coefficients α and β in (8.1) are calibrated based on average levels of historical demand and price recorded in five states of NEM in 2016-2017. The technology characteristics of the incumbent synchronous and intermittent generation capacities existing in NEM are listed in Tables C.1 and C.2, respectively, in Appendix C. Synchronous generators include classical coal, gas, hydro, and biomass plants in addition to the new emerging technology of thermal solar, and the intermittent generators consist of wind farms, PV farms and roof-top PVs. The technology characteristics of different storage types, including pump-hydros, cooperatively controlled and non-cooperative batteries, with their incumbent capacity levels are listed in Table C.3 in Appendix C. Finally, the interconnectors between different states of NEM and their associated characteristics are listed in Table C.4 in Appendix C.

The investment cost of any technology reduces as time goes on with the given de-escalation rates, which are input to our model. Fig. 8.1 shows the trajectory of investment cost reduction of generation and storage technologies [12]. It can be seen that mature generation technologies like coal, gas, biomass and hydro do not show significant investment cost reduction, whereas wind, PV, and thermal solar are expected to have 30%, 42%, and 53% investment cost reduction by 2052, respectively. The largest investment cost reduction is forecast for battery storage technology, which is about 68% by 2052.

8.4.1 Impact of Emission Reduction Policy on Market Expansion

In our study, the coefficient α^{ER}, is set to force 0% up to 100% emission intensity reduction by 2052 compared to 2017. Fig. 8.2 compares the net increase or decrease of capacity for generation, Fig. 8.2(a), storage and transmission, Fig. 8.2(b), technologies by 2052 in NEM, given the emission intensity reduction target. Based on this figure, increasing the emission intensity target up to 45% will not affect the net generation capacity. This is

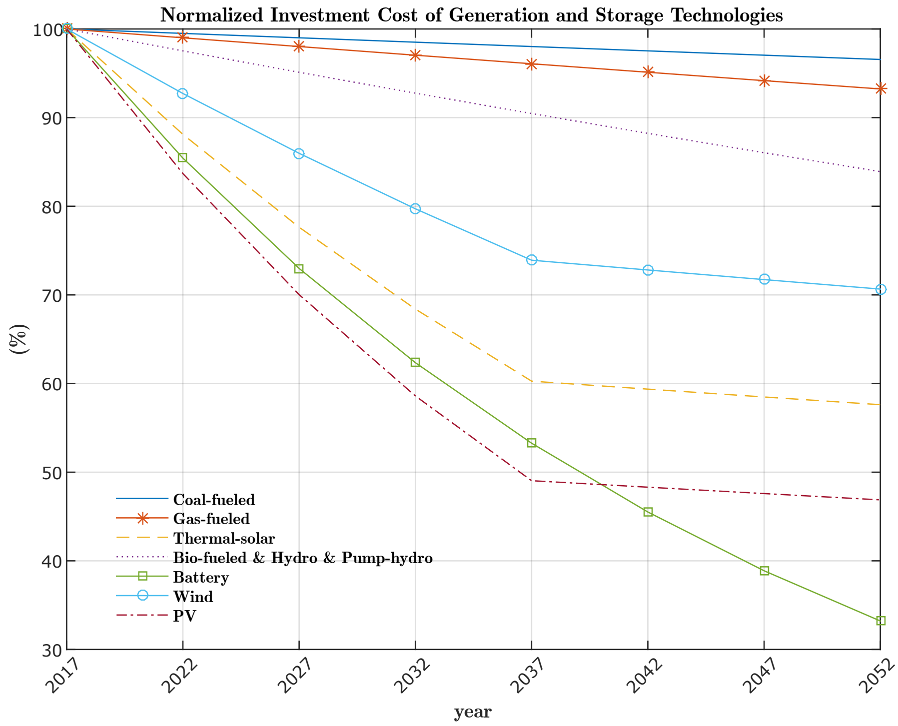

Figure 8.1: Normalized investment cost of generation and storage technologies during 2017-2052 (Normalization is compared to the costs in 2017).

because clean electricity technologies are competitive enough to penetrate and reduce the emission intensity at least by 45% by 2052. However, to achieve a higher level of emission reduction target, it is required to set emission tax/subsidy incentive policies. The emission tax/subsidy incentives lead to accelerate the closure of coal and gas plants, from -10.9 GW and -5.5 GW to -19.9 GW and -8.3 GW, respectively, and the addition of renewable generators, from 9.3 GW to 22.2 GW for synchronous renewables and from 26.8 GW to 40.8 GW for intermittent renewables, in the network by 2052.

The high penetration of intermittent generation technologies is accompanied by high levels of storage in both forms of pump-hydro and cooperatively controlled batteries, which increase at most by 9.5 GW and 12.1 GW until 2052, respectively, and also high levels of interconnector between states, which increases at most by 3.7 GW until 2052. The non-cooperative batteries, which just make profit from energy arbitrage, cannot compete with cooperatively controlled batteries which make profit from both energy arbitrage and fast response support. In high emission intensity reduction target cases, very low level of investment is made on batteries without fast response provision capability (non-cooperative batteries) in the network.

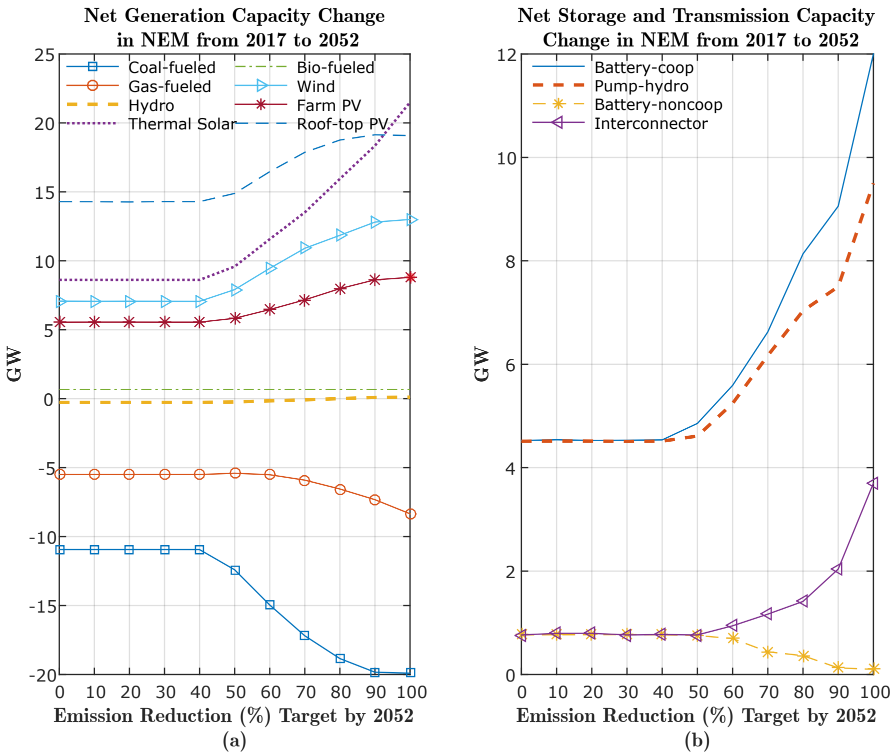

Figure 8.2: Net increase/decrease of capacity for (a) generation and (b) storage and transmission technologies by 2052 in NEM for different target levels of emission intensity reduction.

In the following subsections, we compare our simulation results for just two cases of (i) No Emission Intensity Reduction policy (ii) 80% Emission Intensity Reduction policy in NEM by 2052 (zero emission scenarios in Australia until 2050 and 2070 are discussed in [12]). Note that even in the first case the emission intensity reduces almost by 45%, which means that emission intensity reduction will happen even without any emission policy.

8.4.2 Impact of Emission Reduction Policy on Electricity Prices and Demands

The emission intensity reduction target affects the trajectory of electricity prices and demands in NEM during 2017-2052. Fig. 8.3(a) illustrates the average wholesale prices in

NEM by 2052 with and without implementing the emission reduction policy. It can be seen that the market price is extremely high in 2017, which is the consequence of exercising market power by coal and gas generation firms. The price reduction trend continues for the next twenty years, i.e., until 2037. In fact, investment on renewable technologies increases the competition and reduces the prices for that period. By 2037, a large portion of coal power plants are closed down in our model and the cost of installing new generation capacities rises the wholesale prices again during 2037-2052. Surprisingly, in the price declining period, i.e., 2017-2037, imposing the emission intensity reduction policies comparatively lowers the prices by 5%, which is related to the market power level. Penetration of renewables increases the competition (reduces the market power) and leads to lower prices.

Fig. 8.3(b) compares the average wholesale and net demand levels in NEM by 2052 with and without implementing the emission reduction policy. Note that the net demand includes the roof-top PV generation in addition to the wholesale demand. The divergence of the net and wholesale demand levels is caused by penetration of roof-top PVs in the network. Roof-top PV generation increases by 3.93 times in No Emission Reduction Policy case and by 4.84 times in 80% Emission Reduction Policy case until 2052, which shows that roof-top PV is competent enough to penetrate enormously by 2052 with or without emission incentive policy.

8.4.3 Carbon Tax&Subsidy Design

We design the emission incentives based on the dual variable of the emission intensity constraint, which is called carbon price, at the NE point in our model. Implementing 80% Emission Intensity Reduction policy, the emission intensity must uniformly decrease from the base year level of 0.727 $\text{tonne}_{\text{CO}_2}/\text{MWh}_\text{e}$ in 2017 to 0.145 $\text{tonne}_{\text{CO}_2}/\text{MWh}_\text{e}$ in 2052. Fig. 8.4 (a) shows the calculated carbon price at different years to reach 80% emission intensity reduction by 2052. The carbon price moves upward in the beginning stage, up to year 2032, then decreases during 2032-2042, and goes up again at the final stage, 2042-2052. The closure down of coal and gas power plants, which are at their end of life, mostly happens during 2032-2042, which reduces the emission intensity and carbon price

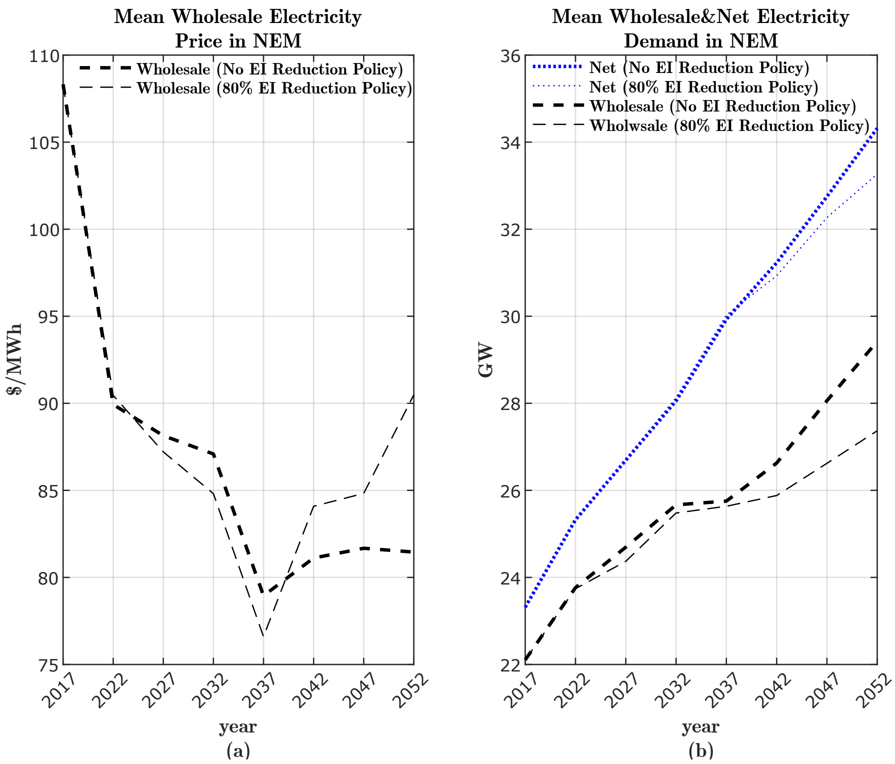

Figure 8.3: The average yearly (a) wholesale prices and (b) net and wholesale demands in NEM, without or with emission reduction policy (net demand =wholesale demand + roof-top PV).

level. However, higher levels of carbon price is calculated in our model to achieve higher levels of emission intensity reduction at the final stage, regarding the uniform reduction of emission intensity from 2017 to 2052.

Fig. 8.4 (b) indicates the average amounts of tax and subsidy that any type of generator pays or receives each year based on their electricity generation emission intensity and the calculated carbon price of that year. As coal-fueled generators have emission intensities much higher than the emission intensity target levels, they always pay carbon tax in the market. The gas-fueled generators have lower emission intensities and do not pay significant carbon penalty until 2042. The renewable generators, including wind, PV, thermal solar, bio-fueled, and hydro, receive the carbon subsidy in the market, as their generation emission intensity is zero. One kW capacity of thermal solar and bio-fueled generators are more efficient in reducing the emission intensity than one kW of wind, PV or even hydro, and thus receive higher emission subsidy in average.

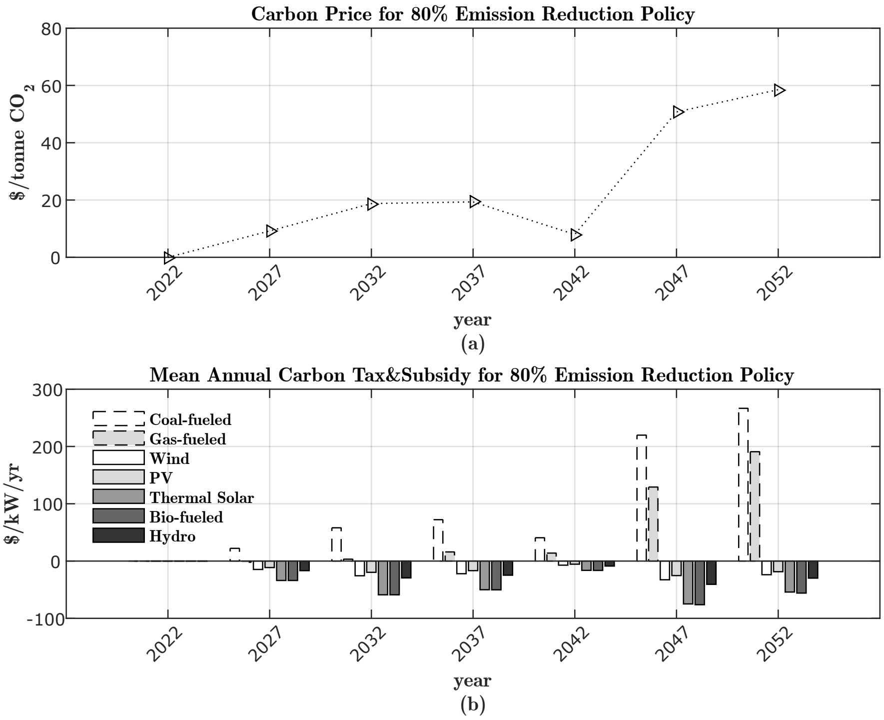

Figure 8.4: The trajectory of (a) carbon price, (b) carbon tax (positive) and subsidy (negative) of different generation types during 2017-2052.

8.4.4 Fast Response Capacity Tax&Subsidy Design

The other tax and subsidy incentive is calculated based on the dual variable of the fast response dispatchable generation constraint at the NE point in our model. Intermittent generators, i.e., wind and PV, are vulnerable to generation fluctuation due to wind and solar energy availability. Therefore, there must be adequate fast response generation capacity to dispatch even out of merit, i.e., even when their marginal cost of generation is above the market price, if wind or solar is lacking. As fast response generators may dispatch out of merit, they need to be subsidized. The subsidy is provided by taxing the intermittent generators. Fig. 8.5 indicates the level of fast response tax and subsidy for different generation types during 2017-2052, with and without emission intensity reduction policy. It can be seen that implementing the emission reduction policy, which leads to higher levels of intermittent generation in the market, we calculate higher amounts of fast response tax and subsidy for all generators. Moreover, the subsidy level is not the same for different generation types. One kW pump-hydro receives higher subsidy for fast response provision than one kW battery as pump-hydros generally have larger energy storage tanks (kWh). However, the battery's fast response subsidy becomes more than the pump-hydro's in 2052 due to the decline in investment cost of the battery tanks. The subsidy on hydro plants uniformly increases by time, but the subsidy on gas-fueled plants increases significantly after 2042, as they have to pay considerable amounts of emission tax at those times.

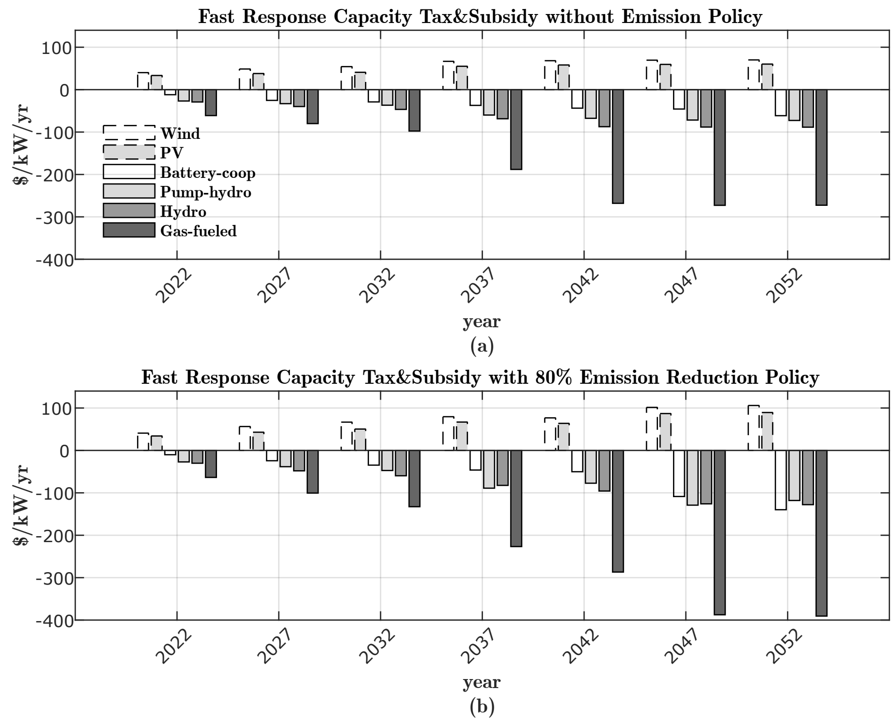

Figure 8.5: The trajectory of fast response capacity tax (positive) and subsidy (negative) for (a) No Emission Reduction policy, (b) 80% Emission Intensity Reduction policy.

8.4.5 Impact of Market Power on Market Expansion

In this subsection, we compare our simulation results with the scenario when market power is disregarded in the game, i.e., a perfectly competitive market. Fig. 8.6 illustrates our simulation results for the generation, storage and transmission capacities in NEM at the end of 2052 with and without market power consideration when there isn't any emission policy, Fig. 8.6(a), and when 80% emission intensity reduction policy is implemented, Fig. 8.6(b). It can be seen that disregarding the market power, the investment on intermittent renewables, i.e., wind and solar PV, reduces almost by 60% in both emission policy cases due to lower market prices. Lower market prices decreases the investment attraction on intermittent renewables. Disregarding the market power results in more investment on synchronous generation, specifically coal and thermal solar in without and with emission reduction policy cases, respectively, in our model. When market power is disregarded, investment on gas generation is almost zero in our model due to its high operation and fuel cost. Investment on storage technologies also decreases without considering the market power.

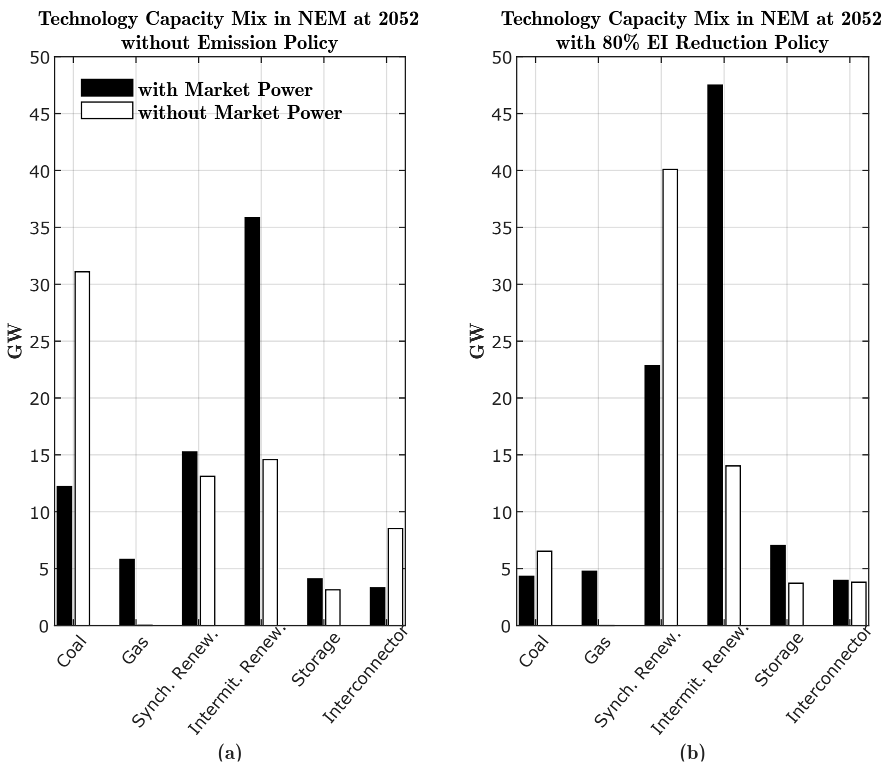

Figure 8.6: Technology capacity mix in NEM with and without considering market power for (a) No Emission Reduction policy, (b) 80% Emission Intensity Reduction policy.

8.5 Conclusion

- Numerous factors, such as technology investment cost, maintenance, operation and fuel costs, and different types of tax/subsidy incentive policies, affect the future generation technology mix in an electricity market. The future of market prices, generation and demand levels are very sensitive to those factors. For instance, the total capacity of non-cooperative batteries, which just make profit from energy arbitrage, is much less than that of the cooperatively controlled batteries, which make profit from both energy arbitrage and fast response service provision, despite having similar investment costs.

- Emission intensity reduction policies do not necessarily increase the average electricity prices all the times. Considering the Emission Intensity Reduction policy in our model, we calculated lower prices relative to No Emission Reduction policy scenario in the market until 2042. We also found that the price increase due to implementing the emission policies after 2042 happens at off peak times and even slightly reduces the peak time prices. This discussion is similar to the recent findings in [68].

- Emission incentive policies, which are calculated based on the dual variable of the emission constraint, can be used to penalize the pollutant generators and to reward the renewables and clean technologies. It is observed in our simulations that the retirement of the incumbent coal-fueled and gas-fueled generators reduces the carbon price level and subsequently the emission incentive policy levels in 2042. Thereafter, carbon price rises again to retain the emission intensity reduction trend in the market.

- The incentive policies of fast response capacity tax and support, which are calculated based on the dual variable of the fast response generation constraint, can be used to penalize the intermittent generators and subsidize the fast response capacities. Gradual retirement of the incumbent gas-fueled plants and penetration of intermittent generators lead to higher levels of subsidy to ensure existence of enough fast response capacity in the market.

- Considering the market power in a market expansion model significantly affects the technology expansion decisions. Disregarding the market power, high electricity prices are not calculated in the model, which does not provide enough incentive for more recent technologies, like intermittent generators and batteries, to highly penetrate in the market.

- The high level of investment on synchronous renewable capacity, like thermal solar, which may have heat energy storage system or may be a hybrid system that use other fuels during periods of low solar radiation, and battery storage can also prevent the inertia and frequency response problems in electricity networks with high level of intermittent generation, as discussed in [15].

In Chapter 9, we summarize the wholesale electricity market models we developed in this thesis and highlight the important findings from this research as dot points.

Chapter 9
Conclusions

9.1 Summary of Chapters and Conclusions

IN THIS thesis, operational and planning Cournot-based wholesale electricity market models are developed and used to analyze the supply, demand and price variations in real-world electricity markets. Australia's National Electricity Market is studied as the case study, which is experiencing high levels of intermittent electricity generation and price volatility in recent years. We extended the existing Cournot-based electricity market models to analyze the price volatility in the market and find how storage can facilitate the integration of renewable electricity in power networks. Moreover, we developed long-term wholesale electricity market models to design tax and subsidy policies required to achieve the emission and dispatchable capacity goals in the market.

In Chapter 2, a classic Cournot-based electricity market model including strategic generation firms is introduced. The model is extended to consider storage and transmission players and states that:

- Strategic storage players maximize their profit from energy arbitrage and the strategic transmission lines maximize their electricity trading profit based on the price difference at their terminals.
- Any regulated generation, storage and transmission player maximizes the market surplus or social welfare, which is the profit or surplus for both generators and consumers, in our model.
- The defined game is developed as a centralized optimization problem to find the

NE solution as the game model just includes linear inverse demand functions.

In Chapter 3, we briefly introduce the National Electricity Market in Australia and explain its pricing mechanism. Then we compare the linear and non-linear inverse demand functions and show that

- Accurate calibration of the inverse demand functions reduces our simulation error terms (comparing to historical price and demand data).

In Chapter 4, a multi-region Cournot-based electricity market model with nonlinear inverse demand functions is developed, which is solved as a Mixed Complementary Problem. The transmission lines are modeled as individual market players likewise the other firms in the game, which leads to far more convenient computations than when the transmission lines are considered as constraints for a market clearing engine. The model is applied to the 5-node NEM market, and is calibrated with realistic data from year 2015. The market is simulated with and without considering a large coal power plant in the game under 365 intermittent energy availability scenarios to find how a base-load power plant closure impacts the market price and volatility. Our simulations in the NEM market show:

- The highest proportional change in average price, peak price and price volatility happens in the region (VIC) where the closure happens and then in its neighboring regions TAS and SA.
- Depending on the capacity of interconnectors, the impact of coal plant closure may differ in different market regions.
- The aggregate CO_2 emission of gas and coal power plants in the market, which is affected by the electricity market prices, reduces by 5.8% after the coal power plant closure.

In Chapter 5, a bi-level optimization model is proposed to find the minimum storage capacity required to achieve a price volatility level in an electricity market. In the upper level problem, the optimal regional storage capacities are found, and in the lower level problem, the Bayes-NE solution of the market under a set of scenarios is calculated. The non-cooperative interaction between regulated/strategic generation, storage and transmission players in the market is calculated using a stochastic Cournot-based game with a non-linear inverse demand function. The exponential inverse demand function is accurate enough to model the impact of storage on reducing the very high prices in the market. The existence of Bayes-NE is established for the lower level problem under the exponential inverse demand function. The bi-level problem is converted into a single level problem as a MPEC and is solved by a greedy algorithm. The simulation results in the NEM market show that:

- Storage alleviates the price volatility but does not remove it completely.
- Regulated storage firms are more efficient in reducing the price volatility than strategic storage firms.
- Although both storage and transmission capacities are able to reduce the price volatility level in the market, regulated storage can effectively alleviate high levels of price volatility when transmission lines are under maintenance.
- As a rule of thumb, a region with highest share of intermittent electricity in its total generation is the candidate to install storage capacity to reduce the price volatility in a multi-region electricity market.

In Chapter 6, a bi-level optimization model is proposed to allocate a fixed budget on regulated storage and wind capacities in order to minimize the weighted sum of average price and price volatility in a single region taking into account the interdependency between different regions. In the upper level problem, the weighted sum of average price and price volatility is minimized by allocating a budget on regulated wind and storage capacities in the specified region. In the lower level problem, a stochastic Cournot-based electricity market model with non-linear inverse demand functions is used to model the non-cooperative interaction between regulated/strategic generation, storage and transmission firms. The bi-level problem is converted into a single-level problem as a MPEC and is solved by a line-search algorithm. Based on our simulations, in the NEM market:

- Both storage and wind are capable of reducing the average price and price volatility, but storage is more efficient in reducing the price volatility and wind in reducing the average price.
- Based on the importance of average price and volatility, a mixed combination of storage and wind can optimally minimize the weighted sum of price and volatility in the market.
- Wind turbine is almost a mature generation technology and is competent enough to penetrate in the market in large scales.
- The future reduction in investment cost of battery storage also enables this technology to penetrate economically in the market in large scales.

In Chapter 7, a long-term stochastic Cournot-based generation expansion model with a carbon cap constraint is developed which considers a set of scenarios due to wind power intermittency. Generation players decide on their long-term capacity addition and retirement as well as their operation in our model considering a carbon cap constraint in the market. The dual variable of the carbon cap constraint at the Bayes-NE point is used to calculate the carbon price in the market. The game model includes linear inverse demand functions and is solved as a centralized optimization problem. The simulation results, in a generic electricity market with three generation firms of coal, gas and wind, show that:

- Carbon cap constraint leads to proportionally more renewable and less fossil-fueled generation capacity in the market.
- Higher tax on carbon emission is required to install renewables when they are highly stochastic.
- The higher levels of carbon tax can be spent on adding storage technologies to encounter intermittency in renewable generation.
- Comparing the strategic and perfectly competitive behaviors for the wind firm, we observe that the coal firm adds more capacity and the gas firm slightly decreases

its new capacity decisions when wind player strategically reduces its new capacity investment plan.

In Chapter 8, a long-term Cournot-based market expansion model with emission intensity reduction and fast response dispatchable capacity constraints is developed. The regulated/strategic generation, storage and transmission players decide on their long term capacity expansion and their operation in the model considering the emission intensity and fast response capacity constraints. Based on the KKT equations of the game, it is explained how dual variables of the emission and fast capacity constraints at the NE point is used to calculate the tax and subsidy policies required to achieve the emission and reliability goals in the market. The simulation results, in the NEM market, shows that:

- Setting emission reduction policies does not necessarily lead to higher prices and even may decrease the electricity prices at peak hours.
- The incentive policies of fast response capacity can ensure existence of enough dispatchable capacity to balance the supply and demand at any time in the market.
- Considering the market power in expansion models leads to high electricity prices and more investment on expensive technologies in the market.

9.2 Future Research

We used the availability factor for any technology in our developed models to consider the maintenance of power plants, storage technologies and transmission lines in our calculations. The availability factor indicates that the corresponding technology is not available during its maintenance time. However, power plants may make strategic maintenance decisions, which can impact the market prices significantly. In future works, the impact of strategic maintenance decisions [22] of power-plants on market prices, especially when a coal plant is closed down, can be studied.

Furthermore, our proposed storage allocation model can be extended by considering the ancillary services and capacity markets. The impact of ancillary service markets [21] and capacity markets [23] on the integration of storage systems in electricity networks is left as an open problem. It is also interesting to study the wind correlation analysis to look at volatility reduction effectiveness in future works. Moreover, future research can include the optimal storage siting problem subject to the line congestion constraint to alleviate the congestion problem.

Although we did not discuss the ancillary service markets in our electricity market models, Cournot-based models are able to find the value of any ancillary services that are provided in the market. For instance, considering a constraint on minimum electricity supply in the market, one can find the value of providing the minimum level of electricity generation at all times in the market. Using the dual value of the minimum supply constraint at the NE point, it can be calculated that how much must be paid to generators in order to provide the minimum electricity supply service in the market. Moreover, considering a constraint on the existence of reserve capacity in the market, one can calculate the value of reserve capacity based on the dual variable of the constraint at the NE point.

Finally, in our developed electricity market models in this thesis, consumers (retailers) are all considered as price taker players, i.e., perfectly competitive firms. However, if a large retailer with load curtailment ability exists in an electricity market, it possesses market power on the demand side and bids strategically to reduce the price. Existence of market power on the demand side may have a counter effect on the exercise of market power on the supply side and may make the market more competitive. To the best of our knowledge, the strategic behavior of consumers in a wholesale electricity markets, i.e., in two sided electricity markets, remains an open problem.

Appendix A
Charging/Discharging

In this appendix, we show that the charge and discharge levels of any storage device cannot be simultaneously positive at the NE of the lower level game under each scenario in Chapters 5 and 6. Consider a strategy in which both charge and discharge levels of storage device i at time t under scenario w, *i.e.* $q^{\text{dis}}_{itw}, q^{\text{ch}}_{itw}$, are both positive. We show that this strategy cannot be a NE strategy of scenario w as follows. The net electricity flow of storage can be written as $q^{\text{st}}_{itw} = \eta^{\text{dis}}_i q^{\text{dis}}_{itw} - \frac{q^{\text{ch}}_{itw}}{\eta^{\text{ch}}_i}$. Let $\bar{q}^{\text{dis}}_{itw}$ and $\bar{q}^{\text{ch}}_{itw}$ be the new discharge and charge levels of storage firm i defined as $\left\{\bar{q}^{\text{dis}}_{itw} = q^{\text{dis}}_{itw} - \frac{q^{\text{ch}}_{itw}}{\eta^{\text{dis}}_i \eta^{\text{ch}}_i}, \quad \bar{q}^{\text{ch}}_{itw} = 0\right\}$ if $q^{\text{st}}_{itw} > 0$, or $\left\{\bar{q}^{\text{dis}}_{itw} = 0, \quad \bar{q}^{\text{ch}}_{itw} = q^{\text{ch}}_{itw} - q^{\text{dis}}_{itw}\eta^{\text{dis}}_i \eta^{\text{ch}}_i\right\}$ if $q^{\text{st}}_{itw} < 0$. The new net flow of electricity can be written as $\bar{q}^{\text{st}}_{itw} = \eta^{\text{dis}}_i \bar{q}^{\text{dis}}_{itw} - \frac{\bar{q}^{\text{ch}}_{itw}}{\eta^{\text{ch}}_i}$. Note that the new variables $\bar{q}^{\text{st}}_{itw}$, $\bar{q}^{\text{ch}}_{itw}$ and $\bar{q}^{\text{dis}}_{itw}$ satisfy the constraints (5.5a-5.5d).

Considering the new charge and discharge strategies $\bar{q}^{\text{dis}}_{itw}$ and $\bar{q}^{\text{ch}}_{itw}$, instead of q^{dis}_{itw} and q^{ch}_{itw}, the nodal price and the net flow of storage device i do not change. However, the charge/discharge cost of the storage firm i, under the new strategy, is reduces by:

$$c^{\text{st}}_i\left(q^{\text{ch}}_{itw} + q^{\text{dis}}_{itw}\right) - c^{\text{st}}_i\left(\bar{q}^{\text{dis}}_{itw} + \bar{q}^{\text{ch}}_{itw}\right) > 0$$

Hence, any strategy at each scenario in which the charge and discharge variables are simultaneously positive cannot be a NE, i.e. at the NE of the lower game under each scenario each storage firm is either in the charge mode or discharge mode.

Appendix B

Regulated Transmission Firms

In this appendix, we show how the objective function of any transmission player in Chapter 6 is generalized to be either strategic (profit maximizer) or regulated (social welfare maximizer). When γ_{ij}^{tr} in (6.9a) is zero, the player maximizes its profit and when γ_{ij}^{tr} is one, the player equivalently maximizes the social welfare (SW). The definition of social welfare, under any scenario w in our problem, is the total surplus of consumers and producers as:

$$\begin{aligned}\text{SW}_w &= \sum_{i,t} \int_0^{y_{itw}} P_{itw}\left(.\right) \partial y_{itw} - \text{Total Costs}_{it} \\ &= \sum_{i,t} \frac{P_{itw}\left(.\right) - \alpha_{it}}{-\beta_{it}} - \text{Total Cost}_{it}\end{aligned}$$

where Total Cost is the total cost of electricity generation, storage, and transmission.

The derivative of the social welfare function respect to q_{ijtw}^{tr}, given the constraint (6.9b), that is, $q_{ijtw}^{\text{tr}} = -q_{jitw}^{\text{tr}}$, is:

$$\frac{\partial \text{SW}_w}{\partial q_{ijtw}^{\text{tr}}} = P_{itw}\left(.\right) - P_{jtw}\left(.\right),$$

and the derivative of regulated term in (6.9a) respect to q_{ijtw}^{tr} is:

$$\frac{\partial \left(\frac{P_{jtw}(.)}{-\beta_{jt}} + \frac{P_{itw}(.)}{-\beta_{it}} \right)}{\partial q_{ijtw}^{\text{tr}}} = P_{itw}\left(.\right) - P_{jtw}\left(.\right)$$

which shows that based on the first order optimality conditions, maximizing the regulated term is equivalent to maximizing the social welfare for the transmission player.

Appendix C
Technology Characteristics

All financial and technical information on intermittent and synchronous generators, storage technologies and Interconnectors are from [12, 54, 97] in Chapter 8.

Table C.1: Financial and Technical Information on Intermittent Generators in NEM.

Generator Type:	wind Turbine	Farm PV	Roof-top PV
Q^{ig}_{2017} (GW)	3.733	0.356	4.826
$\tilde{Inv}^{ig}$ $(\frac{\$}{kW})$ (a),(b)	$2400^{(1.5\%)}$	$2190^{(3.5\%)}$	$2100^{(3.5\%)}$
c^{ig} $(\frac{\$}{MWh})$	5	2	2
d^{ig} $(\frac{\frac{\$}{MWh}}{MWh})$	0.00125	0.00125	0
PL^{ig} (yr)	25	20	20
$\bar{C}^{ig}$ (GW)	n.a	n.a	24.266

(a) Yearly maintenance cost is approximated by 1 percent of investment cost for all generation, storage and transmission technologies in our calculations.
(b) Investment cost de-escalator rate (%). After 2037 the de-escalator used for wind and all the different solar technologies drops to 0.3% since they are considered mature technologies.

Table C.2: Financial and Technical Information on Synchronous Generators in NEM.

Plant:	Q^{sg}_{2017} (GW)	$\tilde{Inv}^{sg}$ ($\frac{\$}{kW}$)(a)	c^{sg} ($\frac{\$}{MWh}$) operation + fuel	PL^{sg} (yr)	R^{up}, R^{dn} ($\frac{\%}{hr}$,$\frac{\%}{hr}$)	A^{sg} (%)	EF ($\frac{t_{CO_2}}{MWh}$)	RA^{sg} ($\frac{TWh}{yr}$)	$\alpha^{sg,FR} \in \{0,1\}$
Black Coal	18.440	4285(0.1%)	3+18	50	10	75	1	n.a	0
Brown Coal	4.730	5715(0.1%)	3+16.5	50	10	75	1.2	n.a	0
Thermal Gas	1.837	1910(0.2%)	7.5+84	30	10	75	0.62	n.a	0
CC Gas Turbine	3.402	2100(0.2%)	6.1+56	30	10	75	0.41	n.a	0
OC Gas Turbine	6.076	1720(0.2%)	9+84	30	100	75	0.62	n.a	1
Solar Thermal with Storage	0	8500(2.5%)	25+0	35	10	75	0	n.a	0
Biomass	1.014	6500(0.5%)	8+42	30	10	75	0	7.8	0
Hydro	5.711	3600(0.5%)	5+0	35	100	70	0	23.96	1

(a) Capital cost de-escalator rate (%). After 2037 the de-escalator used for solar thermal drops to 0.3%.

Table C.3: Financial and Technical Information on Storage Technologies in NEM.

Storage Type:	Pump-hydro	Cooperative battery	Non-cooperative battery
$Q^{st,f}_{2017}$ (GW)	2160	0	0
$Q^{st,v}_{2017}$ (GWh)	21600	0	0
$\tilde{Inv}^{st,f}$ ($\frac{\$}{kW}$)(a)	800(0.5%)	225(3.1%)	150(3.1%)
$\tilde{Inv}^{st,v}$ ($\frac{\$}{kWh}$)	70(0.5%)	225(3.1%)	225(3.1%)
$PL^{st,f}$ (yr)	30	10	10
$PL^{st,v}$ (yr)	50	10	10
η^{dis},η^{ch} (%,%)	85,85	95,95	95,95
A^{st} (%)	70	90	90
$\alpha^{sg,FR} \in \{0,1\}$	1	1	0

(a) Investment cost de-escalator rate (%).

Table C.4: Financial and Technical Information on Interconnectors in NEM.

Interconnector:	SA-VIC	TAS-VIC	VIC-NSW	QLD-NSW
Q^{tr}_{2017} (GW) Forward	510	478	150	800
Q^{tr}_{2017} (GW) Reverse	680	594	500	1400
$\tilde{Inv}^{tr}$ ($\frac{\$}{kW}$)	1000	1600	700	1100
PL^{tr} (yr)	50	50	50	50
η^{tr} (%)	95	95	95	95
A^{tr} (%)	70	70	70	70

Bibliography

[1] A. G. Kagiannas, D. T. Askounis, and J. Psarras, "Power generation planning: a survey from monopoly to competition," *International Journal of Electrical Power & Energy Systems*, pp. 413–421, 2004.

[2] IEA, "Technology Roadmap, Hydro Power," International Energy Agency, Tech. Rep., 2012.

[3] H. Lund and B. Mathiesen, "Energy system analysis of 100% renewable energy systems-The case of Denmark in years 2030 and 2050 ," *Energy*, vol. 34, no. 5, pp. 524 – 531, 2009.

[4] J. C. Ketterer, "The impact of wind power generation on the electricity price in Germany," *Energy Economics*, vol. 44, pp. 270–280, 2014.

[5] D. Wozabal, C. Graf, and D. Hirschmann, "The effect of intermittent renewables on the electricity price variance," *OR spectrum*, pp. 1–23, 2014.

[6] C.-K. Woo, I. Horowitz, J. Moore, and A. Pacheco, "The impact of wind generation on the electricity spot-market price level and variance: The Texas experience," *Energy Policy*, vol. 39, no. 7, pp. 3939–3944, 2011.

[7] D. Chattopadhyay and T. Alpcan, "A Game-Theoretic Analysis of Wind Generation Variability on Electricity Markets," *Power Systems, IEEE Transactions on*, vol. 29, no. 5, pp. 2069–2077, Sept 2014.

[8] S.-J. Deng and S. S. Oren, "Electricity derivatives and risk management," *Energy*, vol. 31, no. 6, pp. 940–953, 2006.

[9] H. Higgs and A. Worthington, "Stochastic price modeling of high volatility, mean-reverting, spike-prone commodities: The Australian wholesale spot electricity market," *Energy Economics*, vol. 30, p. 31723185, 2008.

[10] A. Tishler, I. Milstein, and C.-K. Woo, "Capacity commitment and price volatility in a competitive electricity market," *Energy Economics*, vol. 30, no. 4, pp. 1625 – 1647, 2008.

[11] P. Williams, "Power Price Spike Hits Australia as Coal Plant Shuts Down," March 2017. [Online]. Available: www.bloomberg.com/news

[12] W. Gerardi and P. Galanis, "Emissions mitigation policies and security of electricity supply," Jacobs Group (Australia), Tech. Rep., June 2017.

[13] S. Borenstein, "Understanding competitive pricing and market power in wholesale electricity markets," *The Electricity Journal*, vol. 13, no. 6, pp. 49 – 57, 2000.

[14] "Paris Agreement," *United Nations Treaty Collection*, 8 July 2016.

[15] P. Mancarella, "Power system security assessment of the future National Electricity Market," Melbourne Energy Institute, Tech. Rep., 2017.

[16] X. Hu, G. Grozev, and D. Batten, "Empirical observations of bidding patterns in Australias National Electricity Market," *Energy Policy*, vol. 33, p. 20752086, 2005.

[17] R. Loulou, U. Remne, A. Kanudia, A. Lehtila, and G. Goldstein, "Documentation for the TIMES Model PART I," Energy Technology Systems Analysis Programme, Tech. Rep., 2005.

[18] W. Jing-Yuan and Y. Smeers, "Spatial Oligopolistic Electricity Models with Cournot Generators and Regulated Transmission Prices," *Operations Research*, vol. 47, no. 1, pp. 102–112, 1999.

[19] D. Chattopadhyay, "Modeling Greenhouse Gas Reduction From the Australian Electricity Sector," *Power Systems, IEEE Transactions on*, vol. 25, no. 2, pp. 729–740, May 2010.

[20] W. W. Hogan, "A Market Power Model with Strategic Interaction in Electricity Networks," *The Energy Journal*, vol. 18, no. 4, pp. 107–141, 1997.

[21] D. Chattopadhyay, "Multicommodity spatial Cournot model for generator bidding analysis," *Power Systems, IEEE Transactions on*, vol. 19, no. 1, pp. 267–275, Feb 2004.

[22] ——, "A game theoretic model for strategic maintenance and dispatch decisions," *Power Systems, IEEE Transactions on*, vol. 19, no. 4, pp. 2014–2021, Nov 2004.

[23] D. Chattopadhyay and T. Alpcan, "Capacity and Energy-Only Markets Under High Renewable Penetration," *Power Systems, IEEE Transactions on*, vol. PP, no. 99, pp. 1–11, 2015.

[24] W.-P. Schill, C. Kemfert *et al.*, "Modeling strategic electricity storage: the case of pumped hydro storage in Germany," *Energy Journal-Cleveland*, vol. 32, no. 3, p. 59, 2011.

[25] J. de Hoog, T. Alpcan, M. Brazil, D. Thomas, and I. Mareels, "Optimal Charging of Electric Vehicles Taking Distribution Network Constraints Into Account," *Power Systems, IEEE Transactions on*, vol. 30, no. 1, pp. 365–375, Jan 2015.

[26] W. Saad, Z. Han, H. Poor, and T. Basar, "A noncooperative game for double auction-based energy trading between PHEVs and distribution grids," in *Smart Grid Communications (SmartGridComm), 2011 IEEE International Conference on*, Oct 2011, pp. 267–272.

[27] N. Lu, J. Chow, and A. Desrochers, "Pumped-storage hydro-turbine bidding strategies in a competitive electricity market," *Power Systems, IEEE Transactions on*, vol. 19, no. 2, pp. 834–841, May 2004.

[28] A. Masoumzadeh, D. Möst, and S. C. Ookouomi Noutchie, "Partial equilibrium modelling of world crude oil demand, supply and price," *Energy Systems*, pp. 1–10, 2016.

[29] M. Ventosa, R. Denis, and C. Redondo, “Expansion planning in electricity markets. Two different approaches,” in *Proceedings of the 14th Power Systems Computation Conference (PSCC), Seville*, 2002.

[30] B. E. Hobbs, “Linear complementarity models of Nash-Cournot competition in bilateral and POOLCO power markets,” *IEEE Transactions on Power Systems*, vol. 16, no. 2, pp. 194–202, May 2001.

[31] J. B. Cardell, C. C. Hitt, and W. W. Hogan, “Market power and strategic interaction in electricity networks ,” *Resource and Energy Economics*, vol. 19, no. 12, pp. 109 – 137, 1997.

[32] S. Wogrin, E. Centeno, and J. Barquin, “Generation capacity expansion in liberalized electricity markets: A stochastic MPEC approach,” *IEEE Transactions on Power Systems*, vol. 26, no. 4, pp. 2526–2532, Nov 2011.

[33] A. Masoumzadeh, E. Nekouei, and T. Alpcan, “Long-term stochastic planning in electricity markets under carbon cap constraint: A Bayesian game approach,” in *2016 IEEE Innovative Smart Grid Technologies - Asia (ISGT-Asia)*, Nov 2016, pp. 466–471.

[34] B. Hobbs, C. Metzler, and J.-S. Pang, “Strategic gaming analysis for electric power systems: an MPEC approach,” *Power Systems, IEEE Transactions on*, vol. 15, no. 2, pp. 638–645, May 2000.

[35] E. G. Kardakos, C. K. Simoglou, and A. G. Bakirtzis, “Optimal bidding strategy in transmission-constrained electricity markets ,” *Electric Power Systems Research*, vol. 109, pp. 141 – 149, 2014.

[36] S. J. Kazempour and H. Zareipour, “Equilibria in an Oligopolistic Market With Wind Power Production,” *IEEE Transactions on Power Systems*, vol. 29, no. 2, pp. 686–697, March 2014.

[37] N. Li, C. Ukun, E. M. Constantinescu, J. R. Birge, K. W. Hedman, and A. Botterud, "Flexible Operation of Batteries in Power System Scheduling With Renewable Energy," *IEEE Transactions on Sustainable Energy*, vol. 7, no. 2, pp. 685–696, April 2016.

[38] V. Krishnan and T. Das, "Optimal allocation of energy storage in a co-optimized electricity market: Benefits assessment and deriving indicators for economic storage ventures ," *Energy*, vol. 81, pp. 175 – 188, 2015.

[39] A. Berrada and K. Loudiyi, "Operation, sizing, and economic evaluation of storage for solar and wind power plants ," *Renewable and Sustainable Energy Reviews*, vol. 59, pp. 1117 – 1129, 2016.

[40] W. Qi, Y. Liang, and Z.-J. M. Shen, "Joint Planning of Energy Storage and Transmission for Wind Energy Generation," *Operations Research*, vol. 63, no. 6, pp. 1280–1293, 2015.

[41] M. Sedghi, A. Ahmadian, and M. Aliakbar-Golkar, "Optimal Storage Planning in Active Distribution Network Considering Uncertainty of Wind Power Distributed Generation," *IEEE Transactions on Power Systems*, vol. 31, no. 1, pp. 304–316, Jan 2016.

[42] L. Zheng, W. Hu, Q. Lu, and Y. Min, "Optimal energy storage system allocation and operation for improving wind power penetration," *IET Generation, Transmission Distribution*, vol. 9, no. 16, pp. 2672–2678, 2015.

[43] J. Xiao, Z. Zhang, L. Bai, and H. Liang, "Determination of the optimal installation site and capacity of battery energy storage system in distribution network integrated with distributed generation," *IET Generation, Transmission Distribution*, vol. 10, no. 3, pp. 601–607, 2016.

[44] Y. Zheng, Z. Y. Dong, F. J. Luo, K. Meng, J. Qiu, and K. P. Wong, "Optimal Allocation of Energy Storage System for Risk Mitigation of DISCOs With High Renewable Penetrations," *IEEE Transactions on Power Systems*, vol. 29, no. 1, pp. 212–220, Jan 2014.

[45] R. Walawalkar, J. Apt, and R. Mancini, "Economics of electric energy storage for energy arbitrage and regulation in New York ," *Energy Policy*, vol. 35, no. 4, pp. 2558 – 2568, 2007.

[46] H. Mohsenian-Rad, "Optimal Bidding, Scheduling, and Deployment of Battery Systems in California Day-Ahead Energy Market," *IEEE Transactions on Power Systems*, vol. 31, no. 1, pp. 442–453, Jan 2016.

[47] H. Akhavan-Hejazi and H. Mohsenian-Rad, "A stochastic programming framework for optimal storage bidding in energy and reserve markets," in *Innovative Smart Grid Technologies (ISGT), 2013 IEEE PES*, Feb 2013, pp. 1–6.

[48] H. Mohsenian-Rad, "Coordinated Price-Maker Operation of Large Energy Storage Units in Nodal Energy Markets," *IEEE Transactions on Power Systems*, vol. 31, no. 1, pp. 786–797, Jan 2016.

[49] E. Nasrolahpour, S. J. Kazempour, H. Zareipour, and W. D. Rosehart, "Strategic Sizing of Energy Storage Facilities in Electricity Markets," *IEEE Transactions on Sustainable Energy*, vol. 7, no. 4, pp. 1462–1472, Oct 2016.

[50] X. Fang, F. Li, Y. Wei, and H. Cui, "Strategic scheduling of energy storage for load serving entities in locational marginal pricing market," *IET Generation, Transmission Distribution*, vol. 10, no. 5, pp. 1258–1267, 2016.

[51] A. Awad, J. Fuller, T. EL-Fouly, and M. Salama, "Impact of Energy Storage Systems on Electricity Market Equilibrium," *Sustainable Energy, IEEE Transactions on*, vol. 5, no. 3, pp. 875–885, July 2014.

[52] A. Masoumzadeh, E. Nekouei, T. Alpcan, and D. Chattopadhyay, "Impact of Optimal Storage Allocation on Price Volatility in Energy-only Electricity Markets," *IEEE Transactions on Power Systems*, vol. PP, no. 99, pp. 1–1, 2017.

[53] A. Masoumzadeh, H. Rasekhi, and A. Fathi, "A comprehensive energy supply model in an office building based on the reference energy system," *International Journal of Sustainable Energy*, vol. 35, no. 1, pp. 88–102, 2016.

[54] M. Jeppesen, M. Brear, D. Chattopadhyay, C. Manzie, R. Dargaville, and T. Alpcan, "Least cost, utility scale abatement from Australia's NEM (National Electricity Market). Part 1: Problem formulation and modelling," *Energy*, vol. 101, pp. 606 – 620, 2016.

[55] W. El-Khattam, K. Bhattacharya, Y. Hegazy, and M. M. A. Salama, "Optimal investment planning for distributed generation in a competitive electricity market," *IEEE Transactions on Power Systems*, vol. 19, no. 3, pp. 1674–1684, Aug 2004.

[56] A. S. Chuang, F. Wu, and P. Varaiya, "A game-theoretic model for generation expansion planning: problem formulation and numerical comparisons," *IEEE Transactions on Power Systems*, vol. 16, no. 4, pp. 885–891, Nov 2001.

[57] L. Wang, M. Mazumdar, M. D. Bailey, and J. Valenzuela, "Oligopoly models for market price of electricity under demand uncertainty and unit reliability," *European Journal of Operational Research*, vol. 181, no. 3, pp. 1309 – 1321, 2007.

[58] J. Sirikum, A. Techanitisawad, and V. Kachitvichyanukul, "A New Efficient GA-Benders' Decomposition Method: For Power Generation Expansion Planning With Emission Controls," *IEEE Transactions on Power Systems*, vol. 22, no. 3, pp. 1092–1100, Aug 2007.

[59] C. Unsihuay-Vila, J. W. Marangon-Lima, A. C. Z. de Souza, I. J. Perez-Arriaga, and P. P. Balestrassi, "A Model to Long-Term, Multiarea, Multistage, and Integrated Expansion Planning of Electricity and Natural Gas Systems," *IEEE Transactions on Power Systems*, vol. 25, no. 2, pp. 1154–1168, 2010.

[60] H. Mirzaesmaeeli, A. Elkamel, P. Douglas, E. Croiset, and M. Gupta, "A multi-period optimization model for energy planning with CO2 emission consideration," *Journal of Environmental Management*, vol. 91, no. 5, pp. 1063 – 1070, 2010.

[61] J. Santisirisomboon, B. Limmeechokchai, and S. Chungpaibulpatana, "Impacts of biomass power generation and CO2 taxation on electricity generation expansion planning and environmental emissions," *Energy Policy*, vol. 29, no. 12, pp. 975 – 985, 2001.

[62] I. Das, K. Bhattacharya, and C. Caizares, “Optimal Incentive Design for Targeted Penetration of Renewable Energy Sources,” *IEEE Transactions on Sustainable Energy*, vol. 5, no. 4, pp. 1213–1225, 2014.

[63] Y. Zhou, L. Wang, and J. D. McCalley, “Designing effective and efficient incentive policies for renewable energy in generation expansion planning,” *Applied Energy*, vol. 88, no. 6, pp. 2201 – 2209, 2011.

[64] H. Almutairi and S. Elhedhli, “Carbon tax based on the emission factor: a bilevel programming approach,” *Journal of Global Optimization*, vol. 58, no. 4, pp. 795–815, 2014.

[65] F. H. Murphy and Y. Smeers, “Generation Capacity Expansion in Imperfectly Competitive Restructured Electricity Markets,” *Operations Research*, vol. 53, no. 4, pp. 646–661, 2005.

[66] I. Milstein and A. Tishler, “Intermittently renewable energy, optimal capacity mix and prices in a deregulated electricity market,” *Energy Policy*, vol. 39, no. 7, pp. 3922 – 3927, 2011, special Section: Renewable energy policy and development.

[67] X. Zhou, G. James, A. Liebman, Z. Y. Dong, and C. Ziser, “Partial Carbon Permits Allocation of Potential Emission Trading Scheme in Australian Electricity Market,” *IEEE Transactions on Power Systems*, vol. 25, no. 1, pp. 543–553, 2010.

[68] A. Finkel, “The Independent Review into the Future Security of the National Electricity Market: Blueprint for the Future,” Commonwealth of Australia, Tech. Rep., 2017.

[69] F. Leuthold, H. Weigt, and C. von Hirschhausen, “A Model of the European Electricity Market,” Chair for Energy Economics and Public Sector Management, Dresden University of Technology, Tech. Rep., 2008.

[70] D. P. Bertsekas, *Nonlinear Programming*, 2nd ed. Athena Scientific, 1999.

[71] T. Basar and G. Olsder, *Dynamic Noncooperative Game Theory, 2nd Edition*. Society for Industrial and Applied Mathematics, 1998.

[72] E. Nekouei, T. Alpcan, and M. Brandao, "Controlling multiple batteries on a radial line," in *Power Engineering Conference (AUPEC), 2014 Australasian Universities*, Sept 2014, pp. 1–7.

[73] M. C. Ferris and T. S. Munson, "GAMS/PATH user guide: Version 4.3," *Washington, DC: GAMS Development Corporation*, 2000.

[74] M. P. Moghaddam, A. Abdollahi, and M. Rashidinejad, "Flexible demand response programs modeling in competitive electricity markets," *Applied Energy*, vol. 88, no. 9, pp. 3257–3269, 2011.

[75] P. Graham, S. Thorpe, and L. Hogan, "Non-competitive market behaviour in the international coking coal market ," *Energy Economics*, vol. 21, no. 3, pp. 195 – 212, 1999.

[76] D. Kirschen, G. Strbac, P. Cumperayot, and D. de Paiva Mendes, "Factoring the elasticity of demand in electricity prices," *Power Systems, IEEE Transactions on*, vol. 15, no. 2, pp. 612–617, May 2000.

[77] S. A. Gabriel, A. J. Conejo, J. D. Fuller, B. F. Hobbs, and C. Ruiz, *Complementarity modeling in energy markets*. Springer Science & Business Media, 2012, vol. 180.

[78] AEMO, "An Introduction to Australia's National Electricity Market," Australian Energy Market Operator, Tech. Rep., 2010.

[79] D. Fudenberg and J. Tirole, *Game theory*. Cambridge, Mass. : M.I.T. Press, 1991.

[80] J. M. Morales, S. Pineda, A. J. Conejo, and M. Carrion, "Scenario reduction for futures market trading in electricity markets," *IEEE Transactions on Power Systems*, vol. 24, no. 2, pp. 878–888, 2009.

[81] J. C. Harsanyi, "Games with Incomplete Information Played by "Bayesian" Players, I-III. Part II. Bayesian Equilibrium Points," *Management Science*, vol. 14, no. 5, pp. 320–334, 1968.

[82] AEMC, "Potential Generator Market Power in the NEM," Australian Energy Market Commission, Tech. Rep. ERC0123, 26 April 2013.

[83] G. Kirchgässner and J. Wolters, *Introduction to modern time series analysis*. Springer Science & Business Media, 2007.

[84] X. Fang, F. Li, Q. Hu, and Y. Wei, "Strategic CBDR bidding considering FTR and wind power," *IET Generation, Transmission Distribution*, vol. 10, no. 10, pp. 2464–2474, 2016.

[85] M. J. Neely, A. S. Tehrani, and A. G. Dimakis, "Efficient algorithms for renewable energy allocation to delay tolerant consumers," in *Smart Grid Communications (SmartGridComm), 2010 First IEEE International Conference on*. IEEE, 2010, pp. 549–554.

[86] M. C. Ferris and T. S. Munson, "Complementarity problems in GAMS and the PATH solver," *Journal of Economic Dynamics and Control*, vol. 24, no. 2, pp. 165–188, 2000.

[87] Frontier-Economics, "Generator Nodal Pricing–a review of theory and practical application," Frontier Economics Pty Ltd., Melbourne, Tech. Rep., 2008.

[88] AER, "State Of The Energy Market 2015," Australian Energy Regulator, Tech. Rep., 2015.

[89] AEMO, "Roof-top PV Information Paper, National Electricity Forecasting," Australian Energy Market Operator, Tech. Rep., 2012.

[90] O. Alsac and B. Stott, "Optimal load flow with steady-state security," *IEEE transactions on power apparatus and systems*, no. 3, pp. 745–751, 1974.

[91] A. Masoumzadeh, E. Nekouei, and T. Alpcan, "Impact of a coal power plant closure on a multi-region wholesale electricity market," in *2017 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*, Sept 2017, pp. 1–6.

[92] C. S. Park, G. Kim, and S. Choi, *Engineering economics*. Prentice Hall: Upper Saddle River, NJ, USA, 2007, vol. 22.

[93] Y. Saboohi, "Energy Supply Model: ESM 84," Sharif Energy Research Institute (SERI), Tech. Rep., 2005.

[94] EIA, "Updated Capital Cost Estimates for Utility Scale Electricity Generation Plants," U.S. Department of Energy, Tech. Rep., April 2013.

[95] A. S. Drud, "CONOPT A Large-Scale GRG Code," *ORSA Journal on Computing 6*, p. 207216, 1992.

[96] A. Niklaus and L. Dowling, "Renewables Influence on the Generation Mix and Gas Demand in Western Australia," Australian Energy Market Operator, Tech. Rep., May 2017.

[97] NERA, "Wholesale Electricity Costs in the NEM; A Report for the Australian Energy Market Commission," NERA Economic Consulting, Tech. Rep., August 2013.