ENVIRONMENTAL AND ECONOMICAL ANALYSIS IN ELECTRICITY MARKET PLANNING AND MANAGEMENT

LI XURAN IVAN

Ph.D

The Hong Kong

Polytechnic University

2013

THE HONG KONG POLYTECHNIC UNIVERSITY
香港理工大學

DEPARTMENT OF ELECTRICAL ENGINEERING

ENVIRONMENTAL AND ECONOMICAL ANALYSIS IN ELECTRICITY MARKET PLANNING AND MANAGEMENT

LI Xuran Ivan

A thesis submitted in partial fulfillment of the requirements

for the degree of Doctor of Philosophy

September 2012

CERTIFICATE OF ORIGINALITY

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgement has been made in the text.

____________________(Signed)

LI Xuran Ivan (Name of student)

DEDICATION

To my parents,

Wen Jing LI and Ye Nv FANG

and my wife,

Shu Yun REN

Abstract

The electricity industry around the world has been experiencing significant reforms at an unprecedented pace in its history. Due to the fundamental reforms of the electric power industry, novel electricity market planning and management methods are therefore needed in this open deregulated environment. Furthermore, growing concerns about environmental issues have led to the establishment of many energy and environmental policies, of which the most relevant ones are those derived from the Kyoto Protocol for the reduction of greenhouse gas emissions as well as those promoting renewable energies. Separate and evolving public policy debates are currently shaping electricity market, carbon market, and renewable market without paying adequate attentions to how each market affects the others, though the markets have overlapping goals with respect to the global economic and environmental benefits.

The objectives of this thesis are to address these notoriously problems, and develop several essential electricity market management and analysis models in two main aspects. The first aspect aims at gaining insightful knowledge of price schemes in deregulated electricity markets. As the nowadays electricity market is closely associated with other commodity markets such as fuel market and carbon market, electricity price is volatile and accurate price forecasting model are in great need for market operators. Besides, problems relating to the management and operation of reactive power are actually arising under the trend towards decentralised production of renewable resources. In order to procure reactive support competitively from the markets, it is necessary to quantify the price of the reactive power source output. Based on the outcomes of the first aspect, the second aspect studies the impacts of emission trading on the operation of electricity markets from either generation companies or market operators' point of view. These studies include the consideration of multimarket environment and renewable energy support schemes.

Revolving around these two aspects, the following topics regarding electricity market management and analysis are discussed and investigated in the thesis.

1. Day-ahead electricity price forecasting based on panel cointegration and particle filter
2. A novel value based reactive power procurement scheme in electricity markets
3. Impacts of emission trading schemes on GENCO's decision under multimarket environment
4. Impacts of emission trading and renewable energy support schemes on electricity market operation
5. Multimarket analysis of GENCOs' operations considering emission trading and renewable energy support schemes

In summary, the research reported in this thesis provides a composite framework for environmental and economical analysis in electricity market planning and management. It covers price schemes in deregulated electricity markets for both electricity active power and reactive power, and also impacts of emission trading on the operation of electricity markets. Further studies are expected to explore reactive power management considering emission trading scheme and wind power uncertainties. This research is finished with nine journals papers and ten conference papers produced.

Publications arising from the thesis

Journals:

[1] **X.R. Li**, C.W. Yu, W.H. Chen, A novel value based reactive power procurement scheme in electricity markets, International Journal of Electric Power & Energy Systems 43 (2012) 910-914.

[2] **X.R. Li,** C.W. Yu, S.Y. Ren, C.H. Chiu, K. Meng, Day-ahead electricity price forecasting based on panel cointegration and particle filter, Electric Power Systems Research 95 (2013) 66–76.

[3] **X.R. Li,** C.W. Yu, F.J. Luo, S.Y. Ren, Z.Y. Dong, K.P. Wong, Impacts of emission trading schemes on GENCO's decision under multimarket environment, Electric Power Systems Research 95 (2013) 257-267.

[4] G.Z. Liu, C.W. Yu, **X.R. Li**, F.S. Wen, Impacts of emission trading and renewable energy support schemes on electricity market operation, IET Generation, Transmission & Distribution 5 (2011) 650-655.

[5] **X.R. Li,** C.W. Yu, Zhao Xu, F.J. Luo, Z.Y. Dong, K.P. Wong, A multimarket decision-making framework for genco considering emission trading scheme, IEEE Transactions on Power Systems (Accepted)

[6] **X.R. Li,** C.W. Yu, A review of emission trading: on the impact of electricity market, carbon market and renewable market", International Journal of Energy Engineering (Accepted)

[7] F.J. Luo, Z.Y. Dong, **X.R. Li**, Y.Y. Chen, C.W. YU, Y. Xu, K. Meng, K.P. Wong, Fuzzy adaptive quantum-inspired particle swarm optimization for unit commitment, IEEE Transactions on Power Systems (Submitted)

[8] **X.R. Li,** C.W. Yu, F.J. Luo, S.Y. Ren, Z.Y. Dong, K.P. Wong, Multimarket analysis of genco's operations considering emission trading and renewable energy support schemes, IEEE Transactions on Power Systems (Being prepared)

[9] F.J. Luo, Z.Y. Dong, Y.Y. Chen, **X.R. Li**, C.W. YU, Y. Xu, K. Meng, K.P. Wong, Coordinated dispatch of wind farm with battery energy storage system, IEEE Transactions on Power Systems (Being prepared)

Conferences:

[1] **X.R. Li**, S.Y. Ren, Y. Wu, Multimarket analysis of genco's operations considering emission trading and renewable energy support scheme **(Champion of the IEEE Hong Kong Section 2012 Postgraduate Student Paper Contest)**

[2] **X.R. Li**, S.Y. Ren, Y. Wu, Multimarket analysis of genco's operations considering wind power uncertainty and emission trading **(1st-Runner-up of Postgraduate Section of YMEC Paper Contest 2012, Hong Kong)**

[3] **X.R. Li**, C.W. Yu, F.J. Luo, S.R. Ren, Z.Y. Dong, Y. Wu, M. K. Meng, K.P. Wong, "Decision making model for genco under the emission trading scheme", IEEE Power & Energy Society General Meeting, PES '12, 22 – 26 July 2012, San Diego, California, USA.

[4] **X.R. Li**, C.W. Yu, Impacts of emission trading on carbon, electricity and renewable markets: A review, IEEE Power & Energy Society General Meeting, PES '10, 25-29 July 2010, Minnesota, Minneapolis, USA.

[5] **X.R. Li**, C.W. Yu, S.R. Ren, K. Meng ; G.Z. Liu, Day-ahead Electricity Market Price Forecasting Based on Panel Cointegration Model, IEEE Power & Energy Society General Meeting, PES '10, 25-29 July 2010, Minnesota, Minneapolis, USA.

[6] **X.R. Li**, C.W. Yu, Interaction analysis among electricity market, carbon market and renewable market: A review of emission trading, 8th International Conference on Advances in Power System Control, Operation and Management, APSCOM '09, 8-11 Nov 2009, Hong Kong, China

[7] Y. Xu, **X.R. Li**, Y. Wu, S.S. Shen, Design of an advanced real-time dynamic security assessment tool for blackout prevention in modern power systems **(1st-Runner-up of Postgraduate Section of YMEC Paper Contest 2010, Hong Kong)**

[8] Shuyun Ren, Jun Bi, Y.F. Fung, **X.R. Li**, T.K.Ho, Freeway traffic estimation in beijing based on particle filter, Sixth International Conference on Natural Computation, ICNC '10, 10-12 Aug 2010, Shandong, China

[9] Y.Y. Dai, J. Huang, Y. Xu, **X.R. Li**, Y. Wu, R. Zhang, Real-time frequency security assessment of power system using intelligent system, **(1st-Runner-up of Postgraduate Section of YMEC Paper Contest 2011, Hong Kong)**

[10] S.Y Ren, Y.F. Fung, J. Zhong, **X.R. Li**, T.K. Ho, Freeway traffic estimation based on improved particle filter. 4th IEEE International Conference on Computer Science and Information Technology, ICCSIT '11, 10-12 June 2011, Sichuan, China

Acknowledgements

This thesis is satisfactorily written based on the research work during my PhD study in the Department of Electrical Engineering (EE), The Hong Kong Polytechnic University, Hong Kong from 2008 to 2012. Coming to the Hong Kong Polytechnic University to pursue a PhD has been a richer experience than I could have hoped for. In these years, many persons have given me supports to my research work and my life, and thus they made significant contributions to this thesis. I would therefore like to sincerely acknowledge them.

First and foremost, I would like to express my most sincere gratitude to my chief supervisor, Dr. Chi Wai YU, for giving me an opportunity to reach this goal, for his directions, supports, and advices over the course of my candidature. It is impossible for me to finish this thesis without his enthusiasm, inspiration, and guidance.

Sincere thanks and gratitude are extended to Prof. Fu Shuan WEN, Prof. Zhao Yang DONG, Prof. Kit Po WONG, Prof. Yu Sheng Xue, Dr. Zhao XU, Dr. Ke MENG, Dr. Hon Wing NGAN, who significantly contribute to my research through discussions and suggestions. I also want to extend my gratitude and appreciation to my friends in the Hong Kong Polytechnic University, who have helped me in one way or another.

Special thanks are given to The Hong Kong Polytechnic University for offering me the Research Studentship as the financial support for my PhD study.

Finally, I offer my deepest thanks to my dear parents Wen Jin LI and Ye Nv FANG and my wife Shu Yun REN for their constant love, supports and encouragements through years. They have contributed more to this thesis than they can imagine. I owe them a debt that can never be repaid.

THE HONG KONG POLYTECHNIC UNIVERSITY
香港理工大學

Table of Contents

List of Figures

List of Tables

List of Abbreviations

ACE: Agent-based Computational Economics
AEMO: Australian Energy Market Operator
AGC: Automatic Gain Control
AMI: Advanced Metering Infrastructures
ANN: Artificial Neural Networks
AWNN: Adaptive Wavelet Neural Network
ARMA: Autoregressive Moving Average
ARIMA: Autoregressive Integrated Moving Average
CAA: Clean Air Act
CCEX: Chicago Climate Exchange
CCGT: Combined Cycle Gas Turbine
CER: Certification Emission Reductions
CDF: Cumulative Distribution Function
CDM: Clean Development Mechanism
CHP: Combined Heat and Power
CM: Carbon Market
CO_2: Carbon Dioxide
CO_2 e: Carbon Dioxide Equivalent
DE: Differential Evolution
DER: Distributed Energy Resources
DG: Distributed Generations
DMAPE: Daily Mean Absolute Percentage Error
EA: Evolution Algorithm
ED: Economic dispatch
EM: Electricity Market
ERC: Equivalent Reactive Compensation
EUETS: European Union Emissions Trading Scheme
ETS: Emissions Trading Scheme
FERC: Federal Energy Regulatory Committee
FDE: Fuzzy Differential Evolution
FITs: Feed-In Tariffs
FM: Fuel Market
FNN: Fuzzy Neural Network
GENCOs: Generation Companies
GHGs: Greenhouse Gases
HHV: Higher Heating Value
JFPC: Johansen Fisher Panel Cointegration
JI: Joint Implementation
LLC: Levin, Lin, and Chu
LSM: Least Square Method
MAC: Marginal Abatement Cost
MG: Micro Grid
MW: Megawatt
MWh: Megawatt-hour
NN: Neural Networks
PC: Panel Cointegration
PCPF: Panel Cointegration and Particle Filter
PDF: Probability Density Function
PF: Particle Filter
PHEV: Plug-In Hybrid Electric Vehicle
PJM: Pennsylvania-New Jersey-Maryland
REC: Renewable Energy Credits
RES: Renewable Energy Sources
RESS: Renewable Energy Support Schemes
RGGI: Regional Greenhouse Gas Initiative
RM: Renewable Market
RPS: Renewable Portfolio Standard
RVM: Relevance Vector Machine
SRMC: Short Run Marginal Cost
SVM: Support Vector Machine
TGCs: Tradable Green Certificates
V2G: Vehicle-to-grid
VAR: Volt-Amps-Reactive
WMAPE: Weekly Mean Absolute Percentage Error
WMAPE*j*: WMAPE for period *j*
WMAE: Weekly Mean Absolute Error
WRMSE: Weekly Root Mean Square Error

CHAPTER 1. INTRODUCTION

1.1. Research Background

The electric power industry had been dominated over the years by large utilities, which were engaged in all the activities of generation, transmission and distribution of power. These vertically integrated entities were usually granted monopoly status in defined franchise areas with the obligation to serve all consumers within those territories. Besides ensuring a fair rate return to utilities, the cost-of-service regulation can protect consumers from potential monopolistic abuses. Within the traditional vertical integration structure, centralized power plants with large size units were the most efficient and economical ways to produce and deliver energy to the customers.

However, the electricity industry around the world has been experiencing significant reforms at an unprecedented pace over the past three decades [1]. Due to an increasing efficiency in electricity production and utilization, the traditional, vertically monopolistic structures have been reformed into open and competitive markets. The most significant benefit of this reform is to allow competition among generators to produce electricity. This creates a market environment in the electricity industry, which is considered as a necessity to increase the efficiency of electric energy production and distribution, and to lower prices. Although the deregulation in electricity industry has many benefits, several new challenges are also observed in the market. Due to the fundamental reforms of the electric power industry, traditional planning and management methods cannot revolve these new challenges. Novel electricity market planning and management methods are therefore needed in this open deregulated environment.

The primary goals of establishing an electricity market (EM) are to provide energy securely, reliably and efficiently. While electricity market planning and management usually meet these goals, other valued outcomes including conserving finite resources, maintaining stable and reasonable electricity cost, and protecting the environment are at the stakes. Growing concerns about environmental issues have led to the establishment of several energy and environmental policies, of which the most relevant are those derived from the Kyoto Protocol [2] for the reduction of greenhouse gas emissions as well as those promoting renewable energies. Within the protocol, emissions trading scheme (ETS) is regarded as one of the most important mechanisms to increase the effort of economic efficiency in reducing greenhouse gas emissions. Reduction credit programs, averaging programs and cap-and-trade programs are three basic types of emissions trading programs [3]. In this thesis cap-and-trade programs, inspiriting the implementation of the carbon market, will be investigated. Besides ETS, several other favourable policies have been enacted to incite the use of renewable energy in the power industry. Separate and evolving public policy debates are currently shaping electricity market, fuel market, carbon market, and renewable market without paying adequate attentions to how each market affects the others, though the markets have overlapping goals with respect to the global environmental and economical benefits. All these further developments in the interactive markets have made existing challenges even more complex.

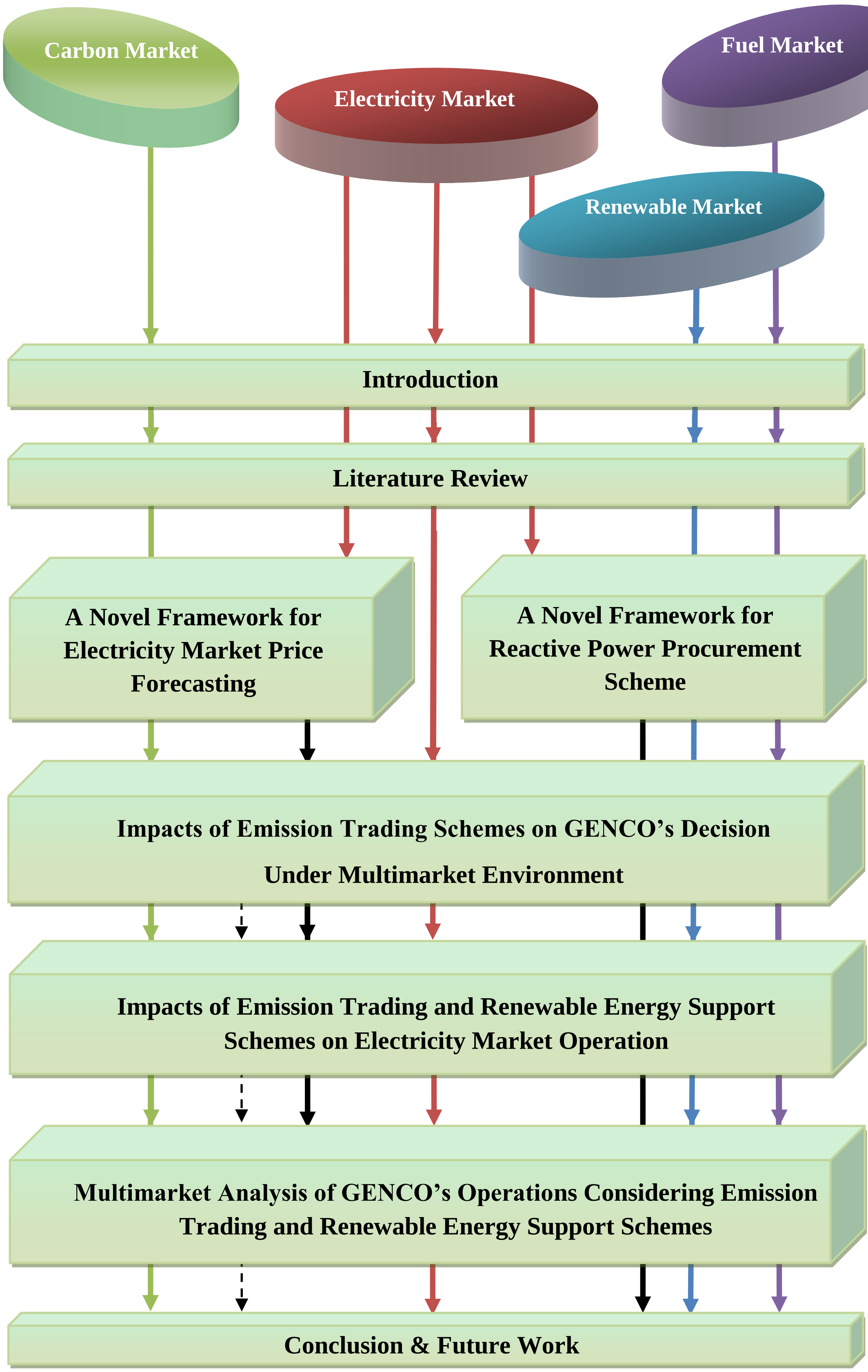

Fig. 1-1 Outline of the thesis

The outline of the thesis is depicted in Fig.1-1, which reveal the linkage of different chapters and the research route. In this thesis novel models, with consideration of environmental and economical influences under multi-market environments, are proposed to address the above notorious challenges in electricity market planning and management. In the following sections, the three closely related markets besides electricity market are briefly introduced first in section 1.2. The research objectives are then presented to identify the tasks of different chapters in section 1.3. It is followed by the description of the organization of this thesis and the linkage among chapters in section 1.4.

1.2. Global Markets Introduction

1.2.1. Fuel market (FM)

Following the deregulation in electricity market, several naturally interrelated fuel markets like coal, oil and natural gas markets [4, 5] have been being developed to more competitive environments. The most significant change is that the prices of these fuel markets are determined by market participants rather than by regulators. This change allows market participants to respond more quickly to affect the fuel prices variation. Specifically, generation companies (GENCOs) in electricity markets are also the main participants in the major fuel source markets. In this manner, GENCOs may respond to price changes in the major fuel source markets (i.e., coal, oil and nature gas markets).

Obviously, the fundamentals of electricity markets and fuel markets are closely related and correlated interactively. Mohammadi [6] demonstrated that there are (1) Stable long-run relationship between real prices for electricity and coal; (2) Bi-directional long-run causality between coal and electricity prices; and (3) Insignificant long-run relationship between electricity and crude oil and/or natural gas prices. Specifically, for electricity markets, electricity spot markets may respond to price changes in its major fuel source markets. Further, fuel source prices may in turn respond to the changes in electricity prices [7, 8]. Along with the potential climate impacts, electricity power industry experiences a significantly shift towards less CO_2-intensive generation technologies. Switching a substantial fraction of electricity generating capacity from fossil fuels to renewable technologies such as wind-powered turbines, geothermal, or biomass, would help to reduce carbon emissions from this sector and satisfy the growing demand for electricity in both developed and developing countries. This trend of diversification is particularly important for electricity market because fossil fuels such as oil and gas are often subject to violent price fluctuations and supply problems. Furthermore, the changes in fuel diversity lead to significant impacts on the fuel market demands. Under the described circumstances, electricity market planning and management need to consider a highly complex scenario, which evolves following market changes based on the offer and demand of energy and fuels. Further research with a more coordinated approach and a better understanding of the links among the diverse factors involved are in urgent needs.

1.2.2. Carbon market (CM)

Internationally, the primary market-based approach is the framework established under the Kyoto Protocol [9]. It sets out an international emissions trading system and two project-based mechanisms, Joint Implementation (JI) and the Clean Development Mechanism (CDM), which together are designed to provide the countries that are parties to the protocol with additional means for meeting emissions targets [2]. These mechanisms are widely applied at the international level. Specifically, emission trading scheme is nowadays regarded as a central pillar of global climate policy. It serves as the inspiration and the basis for the global carbon market. It puts a market value on

Greenhouse Gases (GHGs) emission reductions and creating new markets and investment opportunities.

Carbon markets are forming internationally and nationally and they provide a means for reducing anthropogenic-caused CO_2 emissions and other GHGs. The largest market in place for carbon trading is the European Union Emissions Trading Scheme (EUETS). The EUETS is designed to meet the Kyoto Protocol goals, which have legally binding commitments to reduce GHG emissions for the 148 countries (including all European Union members, Canada and Russia) that have ratified the Protocol [10]. The EUETS officially began in January 2005 and is the largest, multi-country trading scheme for GHGs in the world. In March 2005 alone, more than 6.5 million tons of CO_2 were traded in the EUETS [11]. Recently, several other compliance and voluntary carbon markets have been developed, such as the Chicago Climate Exchange (CCEX) [12], Regional Greenhouse Gas Initiative (RGGI) [13] in the United States, or the Australian scheme [14] in New South Wales. Furthermore, China, one of the developing countries, plans to run regional carbon trading trials in seven most important cities and provinces, namely, Beijing, Tianjin, Shanghai, Chongqing, Guangdong, Hubei and Shenzhen [15].

The booming of carbon market raises increasing concerns internationally. The value of the global carbon market climbs to a new high point in 2011, driven predominantly by a robust increase in transaction volumes. The total value of the market in year 2011 has grown by 11% to US$176 billion, and transaction volumes has reached a new high of 10.3 billion tons of carbon dioxide equivalent (CO_2 e). However, the potential gains have not been fully exploited, because there are numerous obstacles and barriers which prevent the public sector, business and consumers from tapping into that potential. The World Bank estimates that carbon trading globally could be worth US$3.5 trillion by 2020 and it will overtake oil market to become the largest market in the world [16]. The electricity supply industry worldwide has been identified as a major source of greenhouse gas emissions. The combustion of fossil fuels to generate power in electricity supply side contributes mostly the worldwide carbon emission as a single sector [17]. Therefore, further research focused on the integration of CM with other markets e.g EM is an urgent need to exploit the potential of its advantages.

1.2.3. Renewable market (RM)

Over the past decade, markets for renewable energy have been rapidly expanded. It is noticeable that renewable market is not rational to be studied individually since there are several overlaps with either other markets or policies and guidelines issued by government from different regions/countries. The growth being observed in recent years is due to favorable policies that have incentivized renewable, especially wind energy generation.

However, the renewable market under a mandatory one and a voluntary one is classified as an easy access to get a better understanding. Mandatory renewable target is specified and exerted through market mechanism to force a fixed quantum of renewable energy into the supply mix. The implementation of the mandatory renewable market will help increasing the renewable penetration in the electricity industry. For example, Renewable Portfolio Standard (RPS) [16], representing the mandatory market for renewable energy in the U.S., requires electricity generation entities to produce or purchase a certain percentage of their electricity from renewable energy sources by a specified date. Similarly, in order to promote the development of renewable energy, renewable energy support schemes (RESS) have also been implemented in many countries and regions [18, 19]. The objective of the implementation of RESS is to promote rapid development of the renewable energy sources. RESS is traditionally based on three main mechanisms: fixed-price systems, fix-quantity systems and bidding systems. These have been supplemented by other complementary instruments such as investment subsidies, fiscal and financial incentives and green pricing [20].

Along with the existence of several mandatory renewable markets, there are also several growing voluntary markets. On the one hand, a voluntary RM provides measures for consumers (e.g., companies, cities or individuals) who are willing to pay voluntarily more to reduce their carbon footprint, which is the carbon emission associated with one's energy consumptions. On the other hand, the main objectives of these voluntary RMs are to help support green power and to create positive benefits associated with renewable energy as compared to fossil fuels. Besides supporting green power, offsetting the emissions associated with their energy use, reducing the environmental footprint of their operations, or gaining public recognition, these markets are always used to create credits associated with some specified values in many countries or regions.

Such as in the U.S., one renewable energy credits (REC) are tradable, non-tangible energy commodities that represent a proof that one megawatt-hour (MWh) of electricity was generated from an eligible renewable energy resource. Today, more than 50% of U.S. electricity consumers have the option to purchase renewable energy through their utility or electricity provider, generally at a premium above standard electricity rates. In states with restructured electricity markets, customers can choose to switch electricity providers if their current provider does not offer a green energy option. In addition, all customers have the option to purchase RECs separately from electricity through a local or national REC marketer. Generally, these options provide consumers with the ability to purchase renewable energy without the upfront capital costs typically associated with on-site renewable energy systems [21].

To motivate the shift from fossil fuels toward renewables, the appropriate energy policy frameworks enable the power industry to achieve its economic and environmental goals. Mandatory scheme such as RPS and RESS, which constitute the renewable markets, is one of the focuses of this thesis.

1.3. Research Objectives

As discussed in the previous sections, separating and evolving public policy debates are currently shaping electricity market, fuel market, carbon market and renewable market without paying adequate attentions to how each market affects the others, though the markets have overlapping goals with respect to the global environmental and economical benefits. Therefore, taking interactions of different markets into account, this thesis aims at developing novel frameworks for electricity market planning and management.

In competitive electricity markets, energy trading is the main issue and therefore its pricing mechanism is the most significant component. The pricing mechanisms of both real power and reactive power are significant to the efficiency and security of electricity markets. The efficiency of the electricity market means that the ability of the market operation to achieve economic efficiency. The highest economic efficiency occurs when the social welfare is optimized and that the clearing prices equal consumers 'aggregate marginal benefit and suppliers' aggregate marginal cost. The security of the electricity market has received widespread attentions in light of the deregulation of electricity markets. The basic question is whether liberalised markets will secure that adequate capacity is available and whether tight efficiency regulation of electricity networks will result in deteriorating quality of network reliability. Market prices of real power are affected significantly by the fundamentals of other interrelated markets [22]. In addition, pricing mechanisms of reactive power are increasing vital due to the growth of renewable power. This is because the increase of renewable energy penetration leads to security and reliability problems in the power system [23]. Therefore, novel framework for reactive power management needs to evolve. Technical issues should be considered as well as economic issues in market clearing. To gain insightful knowledge of price schemes in deregulated electricity markets, the objective of the first main part of the thesis is to develop novel pricing models for both real power and reactive power. These researches are very useful for enhancing the electricity market planning and management in the deregulated environment.

As the nowadays electricity market is closely associated with other commodity markets such as fuel market and carbon market, electricity price is volatile and accurate price forecasting model are in great need for market operators. Because the market prices usually represent abnormal conditions, two different models should be established to handle price uncertainty. Panel cointegration (PC) model provides a kind of powerful forecasting tool, which utilizes information of both the inter-temporal dynamics and the individuality of interconnected regions. A statistical model based on PC is employed for uncertainty estimation [24]. Furthermore, Particle filter (PF) has achieved significant success in tracking applications involving non-Gaussian signals and nonlinear systems. To make good use of the advantages of the both techniques, this thesis creatively integrates these two technologies and develops an estimation framework. Finally, a two-stage hybrid method is proposed based on panel cointegration and particle filter (PCPF) [25].

In addition to the financial system of the electricity market, the physical power system is another essential component of an electricity market. Reactive power plays an essential role in electricity market planning and operation [26]. The lack of reactive power in the system may cause undesirable voltage drop at some buses. It may result in voltage instability if the power system operator cannot manage the deficiency. It has been proven that problems relating to reactive power management are the main reasons of some major blackouts in the world. Problems related to the management and operations of reactive power are actually arising under the trend towards decentralized production of renewable resources. In order to procure reactive support competitively from the markets, it is necessary to quantify the price of the reactive power source output. Therefore, in this thesis an advanced model is presented for procuring reactive power from reactive resources based on a reactive power pricing structure [27]. The model takes into account reactive power capacity and production cost as well as the value of reactive power.

Based on the outcomes of the first main part of the thesis, the objectives of the latter part of the thesis are to develop novel electricity market planning and management models to investigate how electricity market, fuel market, carbon market and renewable market affect the others. According to my work on the market interaction analysis reported in [22], either carbon market or renewable market attracts policy debates whereas less attention is paid to their interactions. However, raising concerns on the environmental issue have led to significant influences on the power industries’ decision making. The amount of renewables, especially wind power, has reached important penetration rates in power systems nowadays. Furthermore, the utilization of vehicle-to-grid (V2G) [28] brings more alternative options for electricity market planning and management. Currently it is difficult for market participants to make either short term or long term optimal decisions under two or even three interactive markets. Therefore, designing effective methods to handle uncertainties from different markets become timely and valuable tasks. To satisfy the harsh need of electricity market planning and management, the impacts of emission trading on the operation of electricity markets, which includes the consideration of carbon market and fuel market, are studied in [29]. The influences of the two interactive schemes, ETS and RESS, on the electricity market planning and operation, is then presented in [20]. It is then followed by the multimarket analysis considering wind power uncertainty, with carbon market, fuel market and renewable market all taken into account.

Emission Trading Schemes has been implemented in the electricity supply industry. Impacts of ETS on a GENCO's decision making under multimarket environment are firstly investigated. A two-stage model is proposed to assist a GENCO to decide simultaneously the electricity production and trading portfolios during each trading period in the interactive markets.

In order to mitigate greenhouse gas emissions, emission trading and renewable energy support schemes have been or are going to be implemented in some developed countries or regions. Inevitably, the implementation of these two schemes would bring some new problems to electricity market operation. Based on the previous findings, an agent-based market simulation model is needed to be developed in this thesis to account for these two schemes.

Due to the impacts of greenhouse gases on the global warming, many countries are placing enormous pressure on the entire energy industry to reduce carbon emissions. On one hand, several environmental friendly policies like emission trading schemes and renewable energy support schemes have been implemented in the electricity supply industry. On the other hand, exploiting renewable energy is another effective way to mitigate energy source deficiency, control GHGs emissions and achieve smart grid vision. Wind power, being one of the most appealing renewable energy resources, has gained widespread concerns during the last decade. Based on the previous studies in the thesis, a GENCO's decision making is investigated in the thesis considering wind power uncertainty under multimarket environment. However, due to the intermittent and stochastic characteristics of wind resource, a GENCO has to effectively accommodate the wind forecasting errors so as to maximize its profits. A GENCO's behaviour might be different according to the mechanism adopted in the RM. Considering the carbon emission as a changing constraint, an innovative decision making model has to be developed to deal with the multimarket trading problem for a GENCO during each trading period.

Although wind power has many advantages, it suffers seriously from a large amount of uncertainties. It may result in vulnerability of the power system if a system operator ignores the uncertain features of wind power. The variations in wind power generation may lead to system voltage instability and therefore system operators need to consider wind speed volatility in power system planning. Based on the studies of the reactive power procurement pricing scheme in chapter 3, the method to quantify the pricing of reactive power source output when considering wind power uncertainty is planned to be investigated in the future studies. In this case it is able to procure reactive support competitively under the multimarket environment. Furthermore, the utilization of the V2G charger system for both real power and reactive power support to the grid will be prospected in the future work.

To summarize, the major objectives of this research are listed as follows:

- Develop a comprehensive framework that can accurately forecast electricity prices
- Develop a novel value based reactive power procurement scheme in electricity markets

- Investigate the impacts of emission trading schemes on a GENCO's decision under multimarket environment
- Analysis the impacts of emission trading and renewable energy support schemes on electricity market operation
- Develop a novel decision making model for GENCOs considering wind power uncertainty under emission trading and renewable energy support schemes.

1.4. Organization of This Thesis

Following the research route with linkages of different chapters shown in Fig. 1-1, the rest of this thesis is organized as follows:

- Chapter 2 presents a comprehensive literature review on two main parts. The first part reviews the available methods for pricing mechanisms of both real power and reactive power. The current methods that are relevant to this research are classified and their advantages and disadvantages are compared. The second part reviews the investigation on how electricity market, fuel market, carbon market and renewable market affect the others through ETS. The analysis of the impacts of ETS on different markets revolving around the electricity supply industry will be conducted. In view of much works had not been done, studies of future ETS are in an urgent research need. This chapter covers electricity market, carbon market, fuel market and renewable market.
- In chapter 3, a statistical model based on panel cointegration (PC) is employed for uncertainties estimation. Furthermore, particle filter (PF) has achieved significant success in tracking applications involving non-Gaussian signals and nonlinear systems. To make use of the advantages of both techniques, this thesis creatively integrated the two technologies and developed an estimation

framework. Finally, a two-stage hybrid method based on panel cointegration and particle filter (PCPF) is developed. This chapter covers electricity market and focuses on pricing scheme of real power.

- In chapter 4, a novel value based reactive power procurement scheme in electricity markets is developed to quantify the price of the reactive power source output. Problems related to management and operations of reactive power are actually arising under the trend towards decentralized production of renewable resources. The model takes into account reactive power capacity and production cost as well as the value of reactive power. This chapter covers electricity market and focuses on reactive power pricing scheme.
- In chapter 5, a novel dynamic decision making model is proposed to deal with the multimarket trading problem for a GENCO during each trading period. Based on the novel forecasting model developed in Chapter 3, the model enables a GENCO to make a good trade-off between profit-making and emission reduction under the three interactive markets environment. Besides the forecasting method, Differential Evolution (DE) is employed to solve the multi-period stochastic optimization problem and give the optimum results for each time interval. This chapter covers electricity market, carbon market and fuel market and contributes to a comprehensive electricity market planning model for GENCOs.
- In chapter 6, a novel agent-based market simulation model accounting for both emission trading and renewable energy support schemes is developed. Based on the novel forecasting model developed in chapter 3, this chapter employs the Replicator dynamics algorithm to simulate the bidding strategies of agents (generation companies) for profit maximization. The operation process of an

electricity market is simulated over a studied time horizon and some indices are employed to evaluate the market operation performance. Impacts of emission trading and renewable energy support schemes on electricity market operation are investigated through the electricity market planning. This chapter covers electricity market, carbon market and renewable market and contributes to a comprehensive electricity market planning model for market operators.

- In chapter 7, a novel dynamic decision making model is proposed to investigate the decision making of a GENCO considering wind power uncertainty and emission trading under multimarket environment. Wind power, being one of the most appealing renewable energy resources, has gained widespread concerns during the last two decades. The probability of stochastic wind power based on non-linear wind power curve and Weibull distribution are incorporated in the model to examine the two most important mechanisms of RESS (feed-in-tariffs and fixed premium systems). Based on the novel forecasting model developed in chapter 3 and decision making model developed in chapter 5, the model enables a GENCO to make a good trade-off between profit-making and emission reduction under the three interactive markets environment. Comparisons among different scenarios demonstrate the economic and environmental influences of different policies on a GENCO. This chapter covers electricity market, carbon market, fuel market and renewable market and contributes to a comprehensive short term electricity market planning model for GENCOs.
- Chapter 8 concludes this thesis with a summary of the results of this research, followed by the discussions of future work. Following the research route, I will plan to investigate how to quantify the price of reactive power source outputs when considering wind power uncertainty based on the findings in chapter 4. In

this manner, it is able to procure reactive support competitively under the multi-market environment. This is of importance for the power system planning and operation with the increasing penetration of renewable power. Besides, I will also try to examine the utilization of V2G charger system for both real power and reactive power support to the grid. This chapter covers electricity market, carbon market, fuel market and renewable market and contributes to diversified directions of future research.

CHAPTER 2. LITERATURE REVIEW

2.1. Introduction

A comprehensive survey of the state-of-the-art research, which investigates the electricity pricing mechanisms and analyses the interactive markets, is given in this chapter. The relevant literature review comprises broadly three parts outlined below. In the first part, the existing research on the pricing mechanisms of both real power and reactive power are discussed. Current methods that are relevant to the pricing mechanisms will be classified and compared. Afterwards, the second part will explore some fundamental issues of emission trading scheme (ETS). ETS plays a significant role to link the four interactive markets concerned in this thesis. Finally, in the third part, a comprehensive interaction analysis is conducted to explore how electricity market, fuel market, carbon market and renewable market affects the others through the implementation of ETS.

2.2. Pricing Mechanism in Electricity Market

2.2.1. Importance of the pricing mechanism

In an electricity market, the pricing mechanism is the most significant component in its economical operation framework. This economic operation consists of two aspects: active power regulation and reactive power dispatch. Their performances can affect competition, efficiency, consumer surplus and total revenue of the participants in energy markets.

The price mechanism of the active power is reviewed first. The most important issue of the active power price mechanism is price forecasting. It has become more and more significant for all market participants in electricity markets. It provides critical information to build effective planning for the market participants, especially generation and retail companies. In a long term horizon, electricity price forecasting can help market participants to make their decisions. Performance of market planning such as transmission expansion, distribution planning, generation augmentation, and regional energy trades is influenced significantly by the long term electricity price forecast results [30]. In medium-term planning and operation, either producers or consumers can make decision with the help of the medium-term price forecasts to find out how much energy is to be sold/brought through physical bilateral contracts and how much energy is to be sold/brought to/from the pool. In the short term planning, an accurate price forecasting enables power suppliers to build their bidding strategies to achieve the maximum benefit in the spot market. For consumers, they can derive their plans to maximize their utilities using the electricity purchased from the pool, or use self-production capability to protect themselves against high prices. If the electricity market price can be predicted accurately, generators and retailers can reduce their risks and further maximize their profits. From every aspects of the electricity market planning and operation, an efficient and robust price forecasting method is in an essential need. An innovative electricity price forecasting method having the advantages of both panel cointegration and particle filter is developed in chapter 3. Indices such as MAPE, MAE and RMSE are adopted to measure the robustness of the forecasting method.

The price mechanism of the reactive power is then reviewed. It is well known that reactive power plays a crucial role to support active power. Sufficient reactive power support ensures the transfer of active power while maintain system voltages within proper limits. In the vertically integrated electricity industry, retail customers have to pay for the costs of reactive power support, which are included in the bundled electricity prices. In competitive energy markets, it is required to maintain the necessary balance between generation and load in real time to maintain voltages within the required ranges and to transmit active power. To achieve this requirement, reactive power is one of the most important ancillary services in power system. Investigating the cost of providing reactive power service and establishing an appropriate pricing structure are important both financially and operationally for reactive power procurement [31].

In this section, the available electricity forecasting methods are firstly reviewed and compared in section 2.2.2, followed by the discussion of reactive power procurement and pricing in section 2.2.3.

2.2.2. Electricity price forecasting

The importance of the electricity price forecasting has been clarified in section 2.2.1. In an electricity market, major parts of the total energy trading are handled in the day-ahead market. Power suppliers always incline to adjust their bidding strategies to achieve their maximum benefits according to the day-ahead pricing information, though the subsequent short term market mechanisms (such as intraday markets, ancillary services and real-time markets) to provide the balance between energy supply and demand. Similarly, consumers can make their own decisions to optimize their electricity purchased plan in the electricity market, or use self-production capability to protect themselves against high prices [32, 33]. Furthermore, following the research route depicted in Figure.1-1, chapters 5, 6 and 7 dedicate to propose planning and operation models for Generation Companies (GENCOs) under different market environments. The efficiency of these models is highly dependent on the accuracy of electricity price forecasting in the day-ahead electricity market. Consequently, this section conducts a comprehensive survey on the available methods of day-ahead electricity price forecasting.

Electricity price has complex characteristics, which correlates with the complicated bidding strategies linked with the gaming by market participants. It features with non-stationary behaviour, hard nonlinear behavior, high frequency, multiple seasonality, calendar effect, high volatility and high percentage of unusual prices. All these result in the development of an accurate day-ahead electricity price forecasting tool is a challenging task. The revolution of smart grid is driving the development of novel price forecasting techniques for electricity market operations and power system analysis. Along with the applications of advanced metering infrastructures (AMI), users' information can be collected and sent to analysis centers and, at the same time, price signals can be sent back to consumers. This interactive two-way communication pattern may influence the manner of electricity consumption significantly, making the system profiles become more fluctuant and unpredictable. Furthermore, the nowadays interconnected smart grid coordinates the movement of electricity through different regions. The uniform electricity market price is affected significantly by regional loads because electricity price is calculated based on the consideration of the entire grid [24]. On the other hand, the variability of the uniform price can influence the energy-usage patterns and introduce new trends.

The available forecast methods can be broadly classified into three categories: system simulation models, power market equilibrium analysis and time series models [24, 34], as shown in Fig. 2-1.

System simulation models usually concentrate on detailed insight of price formation [35]. Factors such as actual dispatch according to system operating requirements and transmission constraints are considered. Market equilibrium analysis, on the other hand, involves economics and game theory [36]. In addition to the forecasted prices, these two categories always come up with general equilibrium or market strategic behaviors. Time series models are widely adopted to forecast electricity price. Electricity price is forecasted through statistical methods with little attentions paying to the reasons of the price changing. This type of methods can be divided into three subtypes, namely regression based models, stochastic time series models and intelligent learning models.

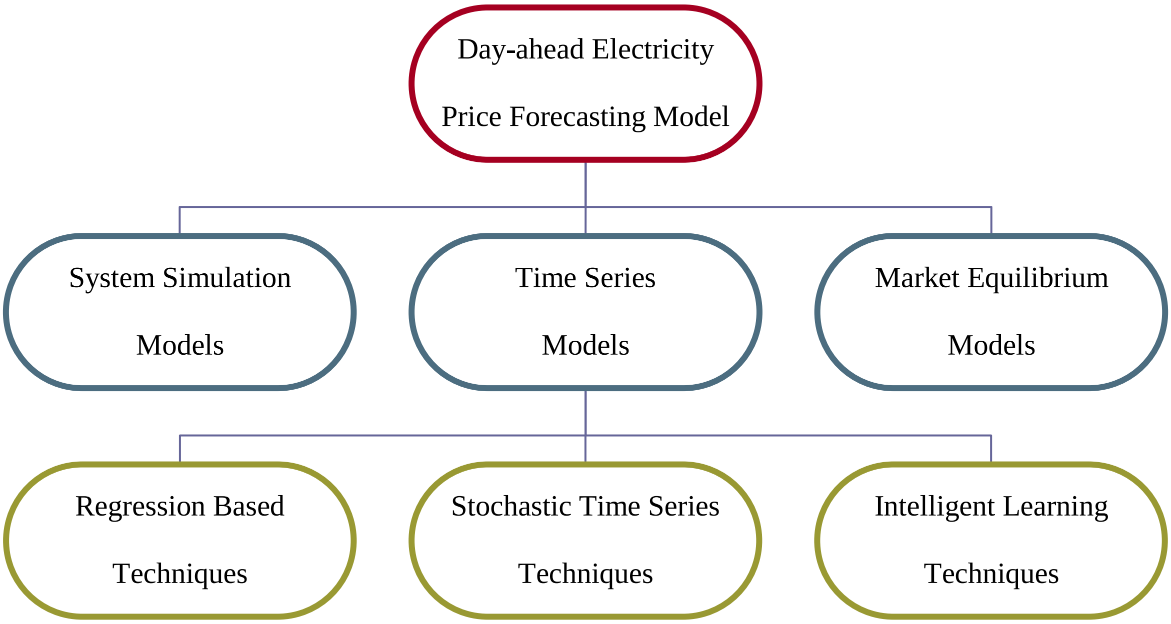

Fig. 2-1 Classification of price-forecasting models

Regression based techniques analyze the assumed relationship between electricity price and a number of independent variables that are known or estimated [37]. These methods overcome serial correlation problems. However, they do not always work well in practice since they assume the variables are stationary or stationary after the application of statistical techniques such as differencing.

Stochastic time series techniques are proposed to deal with nonstationary time series. Both autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) models work by iteratively identifying a parametric model from hypothesized models and estimating the corresponding parameters based on observations. When the series have high volatility and price spikes, GARCH model is a good alternative because it considers conditional variances as time dependent. However, the identification and estimation of these models can be badly distorted by large and sudden price movements within a short period (known as outlier effects). Studies in [38, 39] indicated that outliers can have dominating and deleterious effects on stochastic time series models such as ARMA and GARCH.

Intelligent learning techniques derived from Neural Networks (NN) and data mining have also been studied. Artificial neural networks (ANN) are defined as information processing systems which have common specific characteristics associated to biological networks. ANN is capable to model nonlinear input/output mapping functions. Its families have strong fault tolerance ability though they usually require long training time. A standard ANN is a group of interconnected neural processing units imitating the brain activation. Recent studies on ANN focus on the determination of the best forecasting model by comparing various neural architectures, applying several decomposition techniques or selecting proper transfer functions [40]. L. Wu et al. [41] proposed a hybrid time-series and adaptive wavelet neural network (AWNN) model, composed of linear and nonlinear relationships of prices and explanatory variables, for day-ahead price forecasting. AWNN was used to present the nonlinear, nonstationary impact of load series on electricity prices. Amjady et al. [42] developed a fuzzy neural network (FNN) which combined fuzzy logic and standard ANN to provide more accurate results than ARIMA, wavelet-ARIMA, multilayer perceptron and radial basis function neural networks. Kernel-based machine learning method such as support vector machine (SVM) [39] has shown good accuracy and efficiency in some real-world problems. Furthermore, relevance vector machine (RVM) [39] has been proved outperforms SVM in both the forecast accuracy and computational efficiency. However, the performance of these machine learning models relies on heuristics, e.g., the choices of kernel and penalty functions.

Summarizing the above discussions, day-ahead electricity price forecasting is of importance to electricity market planning and operation. Besides, forecasting day-ahead electricity prices is a complex task, because a price series is a highly volatile series with non-constant mean and variance due to its non-storable nature and stiff condition of maintaining real-time balance of demand and supply of electricity [43]. Available methods have their own demerits so that they cannot effectively deal with price forecasting in the electricity market. Furthermore, following the research route depicted in Fig.1-1, chapters 5, 6 and 7 plan to propose planning and operation models for Generation Companies (GENCOs) and operators under multi-market environments. Having a robust and accurate prediction model for day-ahead electricity price is particularly essential under these circumstances. Therefore, a panel cointegration model is applied to predict day-ahead electricity prices in chapter 3. This is the first time that this economic model is applied to electricity price forecasting. Afterwards, a hybrid model, which combines the advantages of panel cointegration and particle filter, is proposed.

2.2.3. Reactive power pricing

This subsection is concerned with reactive power pricing in the electricity market environment. In order to procure reactive support competitively from the markets, it is necessary to quantify the price of the reactive power source output. It is significant to analyze the cost of providing reactive power service so that an appropriate pricing structure for procuring reactive support can be established. This is of importance to operate the electricity market economically and securely. Furthermore, following the research route depicted in Fig.1-1, a novel decision making model, considering wind power uncertainty, is developed in chapter 7 for GENCOs under multimarket environment. The implementation of either the carbon market or the renewable market will help increasing the renewable penetration in the electricity industry. The penetration of the wind energy in electrical system is therefore rapidly increasing.

Although wind power has many merits, its intermittent and volatile nature has significant influences on the distribution system voltages, frequency and generation adequacy. All these bring more tasks in the electricity market planning and operation and therefore reactive power procurement becomes particularly important. Consequently, this subsection conducts a comprehensive survey on the available methods of reactive power procurement and pricing.

In vertically integrated power systems, the utility concerned company controls all available reactive power sources so that reactive power management is part of the system operator's activities and the expenses incurred for providing such supports are included within the electricity tariff charged to end users. Consequently, less attention needs to be paid to power procurement and pricing.

In the deregulated electricity market environment, reactive power management appears more difficult since different entities are involved in the reactive power support and hence equity is an important factor to be considered for equitable procurement of reactive power support as well as cost allocations among different entities. Intuitively, ensuring sufficient reactive power resources for maintaining required level of voltages is becoming an increasingly difficult issue. It is because electricity resources are dispersed due to the disintegration of the electricity structure. Specifically, in the traditional vertically integrated power industry, when and which electricity resources such as generating reactive power and transmission reactive power shall be dispatched are determined by the control center. This is because the utility company owns all concerned resources so that it can dispatch resources economically. In the new environment, reactive power may be provided by generating entity, transmission entity, and operator, separately. Moreover, these three entities may have different and even conflicting goals. Either of them is not willing to sacrifice their revenues from the sale of active power to produce reactive power unless receiving appropriately compensations. In particular, owners of generators providing reactive power resources will be driven, in competitive generation markets, to maximize their own benefits from their resources. Thus, an incentive mechanism appears necessary for the owners of reactive power sources to provide reactive power support services, and such a mechanism implies an adequate payment that guarantees the economic feasibility of this business [26]. There are some disputes on if or not all kinds of reactive power resources should be compensated, and no generally applicable answer is available for this question since this should be dependent on the specific market models employed. In USA, only reactive power generator sources are entitled to such compensation by *Federal Energy Regulatory Committee* (FERC), in the form of ancillary service payment, as described in [44]. The revolution of smart grid is driving the development of reactive power procurement and pricing for electricity market operations and power system analysis. Along with the applications of advanced metering infrastructures (AMI), users' information can be collected and sent to analysis centers. Meanwhile, price signal can be sent back to consumers. In this case, consumers are allowed to procure their electricity needs from bilateral contracts, spot market, or from self-production facilities. This interactive two-way communication pattern may influence the manner of electricity consumption significantly and lead to more unstable and unpredictable system status.

Researches on the methods for procuring and pricing reactive power have become active in the past decade. P. Frías et al. [45] propose a competitive reactive power provision mechanism. It is developed based on an annual VAR capacity auction. Two market products to be negotiated are identified firstly. They are (a) capacity for reactive power generation, and (b) capacity for reactive power absorption. The market participants, therefore, can bid either for the quantity and the price of the reactive power productions. Then the reactive capacity is assigned to the market participants according to specific requirements for the service procurement set by the system operator. This assignment is made using an optimization algorithm that minimizes the cost of the required VAR sources together with other system security cost. The reactive power provision mechanism guarantees the secure operation under normal and certain pre-selected contingencies. In [46], a unified framework for reactive power management in deregulated electricity markets using a two-settlement model approach is proposed. The proposed model works at two hierarchical levels and in different time horizons; the first level is the procurement market model which works in a seasonal time horizon, while the second level is the dispatch model which works in a 30 min to 1 hour time period. Reference [47] uses a nodal reactive power pricing method to design a price structure to provide compensation to reactive power sources. Using this method, the compensation includes only the production cost. Therefore, it represents only a small portion of the true costs of providing the reactive power service. Moreover, the volatility of the nodal prices for reactive power is also a problem of applying nodal pricing methods to reactive power. In order to avoid the above two problems, the capacity cost should also be taken into account. N. Dandachi et al. [48] introduced a procurement method in which about 80 percent of reactive power cost is recovered from the reactive power capacity payment and the rest from the actual reactive power production. The above references consider reactive power from the costing point of view. However, reactive power needs to be provided locally and the value of the reactive power is not the same everywhere in the system. Thus, reactive power procurement should be determined not only based on the cost. In essence, reactive power value measures the relative importance of the reactive power sources. Equivalent reactive compensation (ERC) method [49] is a useful and practical method to evaluate the reactive power value.

Much of the literature on reactive power pricing builds on the marginal cost theory, which has been applied in real power spot prices. In-depth theoretical discussion on applying the marginal cost concept for real time reactive power pricing was provided in [50]. Detailed cost models of reactive power support can be found in [51] and a similar approach based on the opportunity cost of dispatching reactive power was adopted in [52]. However, the application of marginal reactive pricing is not very practical owing to the volatility and erratic behaviors of this pricing mechanism. From the economic point of view, the "marginal cost price" concept represents the practice of setting the price of a product equal to the extra cost of producing an extra unit of output. This concept contributes a lot to active power pricing. However, it has some disadvantages when applying to reactive power pricing because marginal cost pricing is subject to the problem of reconciling marginal cost prices with the cost recovery requirement. Another approach is to formulate the reactive power pricing as a reactive support cost allocation problem. Electric circuit theories [53], reactive power tracing [54], graph theory [55], harmony search algorithm [56], modified Y-bus method [57], Aumann-Shapley method [58], and ant colony search algorithm [59] are in this category. These methodologies attempt to charge system participants by determining the reactive power that each generator contributes to each individual load. However, real and reactive flow coupling in a transmission network makes the calculation of contributing factors using these methods subjective to a certain extent. Hence, pricing the reactive power in a deregulated power system is a complicated issue. There is a general consensus that there should be a separate reactive power market to manage the provision of reactive power. Owing to the importance of reactive power services for system reliability and the complexity of such services, a significant degree of obligation and centralized control are needed in this market.

Summarizing the above discussions, reactive power procurement and pricing is of importance to the electricity market planning and operation. Different from the situation in vertically integrated power systems, there are lots of difficulty of procuring and pricing the reactive power efficiently in the competitive market environment. Several available literatures on reactive power pricing were built on the marginal cost theory. Therefore they cannot effectively deal with real spot prices in the electricity market. Following the research route depicted in Fig.1-1, pricing schemes for both active power and reactive power are investigated in chapter 3 and chapter 4, respectively. In chapter 4, a novel value based reactive power procurement scheme in electricity markets is developed to account for reactive power capacity and production cost as well as the value of reactive power. Future work described in chapter 8 will plan to examine how to quantify the price of the reactive power source output when considering wind power uncertainty so that it is able to procure reactive support competitively under the multi-market environment.

2.3. Emission Trading Scheme

Having discussed pricing mechanisms for both active power and reactive power which can assist electricity market planning and operation, this section will pay attentions on some fundamental issues of ETS. The mechanism which plays the significant role to link the four interactive markets is emission trading scheme (ETS). It is one of the main focuses of this thesis. Fig. 2-2 indicates the interactions of the four markets through the implementation of ETS. Before the comprehensive markets interaction analysis described in section 2.4, the background of ETS and the international situation of carbon markets are firstly introduced in sections 2.3.1 and 2.3.2, respectively. Research problems of implementing ETS are then presented in section 2.3.3, followed by the comparisons of ETS with other climate policies in section 2.2.4.

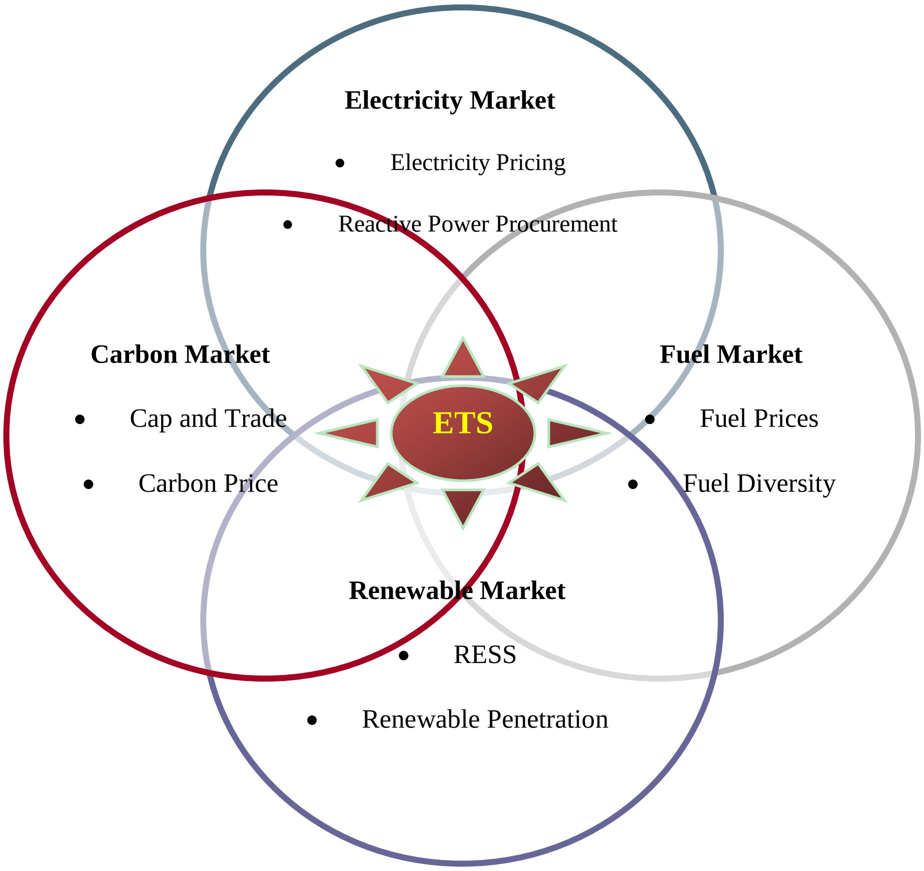

Fig. 2-2 Markets interactions through ETS

2.3.1. Background of emission trading scheme

ETS is an administration approach used to control pollution by providing economic incentives for achieving reductions in the emissions of pollutants. It may also internalize the environmental cost to pollution generators effectively. According to the Coase's theory [60], environmental cost is mainly caused by pollution reductions. For pollution industry such as power plant, the cost can also include the investment on renewable technologies. Besides, this cost also includes the damage cost that power plants pay for the emission of pollution. The nature of internalization of environmental cost is to reflect the external cost of power resources in electricity price [61]. To mitigate pollution effectively, ETS sets a limit which grants rights to emit greenhouse gases to the atmosphere, to reduce pollution over time to the level that prevents any net accumulation in the atmosphere. Milestones in evolving the ETS are shown in Fig. 2-3.

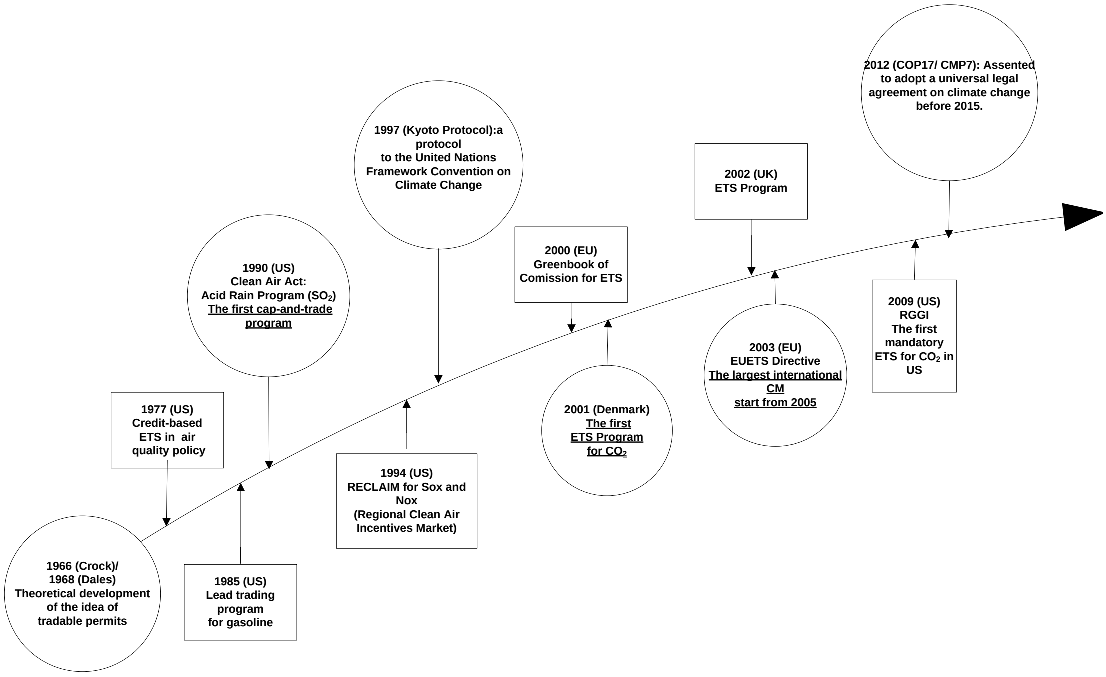

Fig. 2-3 Milestones in the evolution of the ETS

The evolving of the ETS over the course of its history can be divided into four phases:

A. *Gestation:* J. H. Dales proposed a theoretical basis of the ETS in 1968, followed by the further development contributed by W.D. Montgomery in 1972. Then United States Environmental Protection Agency improved it with "flexible regulation" later.

B. *Proof of Principle:* The success of Clean Air Act (CAA) in 1977 has proved the feasibility of the ETS. This is the first development towards trading of emission certificates based on the "offset-mechanism".

C. *Prototype:* United State Acid Rain Program is regarded as the first "cap and trade" system. It was officially announced as a paradigm shift in environmental policy to bring together environmental and industrial interests in the United States. Its great success made the industry more confident in the application of cap-and-trade program.

D. *Mature:* Inherited from the US clean air policy, ETS was developed to a global climate policy in the European Union in 2005. The establishment of EUETS has been considered as an emerging global carbon market which explored a new era for "carbon industry [9, 62-68]. More recently, the 17th Conference of the Parties in Durban (COP17) delivered a breakthrough on the international community's response to climate change, which reached a consensus to draw a universal legal agreement on climate change before 2015 [69].

ETS allows its participants to reach a given environmental objective at the lowest cost via the market forces equilibrium. To illustrate the economic theory of ETS, a simplified two-GENCO case is presented in Fig. 2-4.

Under ETS, a GENCO can make its own planning in fulfilling the emission reduction target. It can reduce all the required amount of emissions by itself and sell the allowance in the market. On the other hand, it can buy the allowance in the market to cover its own produced emission. Furthermore, it can make a reasonable tradeoff between emission reduction and allowance trading. It is assumed that $GENCO_1$ can abate its CO_2 at a much cheaper cost than $GENCO_2$, thus MAC_1 < MAC_2 where MAC (Marginal Abatement Cost) curve of $GENCO_2$ is steeper (higher slope) than that of $GENCO_1$. Therefore, at the current market price of CO_2 allowances P, $GENCO_1$ would abate emissions until the MAC_1 curve intersects with P. The additional reduction helps reducing burden of $GENCO_2$'s total required abatement since it would buy emissions allowance from $GENCO_1$ at price P. $GENCO_1$ makes a profit by abating more emissions than that required. It meets the regulations by abating all of the emissions that is required (R_{Req1}). Additionally, GENCO$_1$ sells its surplus allowance to GENCO$_2$ at price P for every unit. The area (R_{Req1}-1-2-$R*$) in the graph represents its total revenue, while the area (R_{Req1}-3-2-$R*$) represents its total abatement cost. Therefore the "Gains from Trade" (Δ_{123}) is the net benefit when GENCO$_1$ sells the emission credits. On the other hand, the total R_{Req2} of GENCO$_2$ is reached from the internal abatement and the allowances it buys in the market from GENCO$_1$. "Gains from Trade" (Δ_{def}) represents GENCO$_2$'s profits from purchasing allowances in the market. GENCO$_2$ spends less in purchasing this amount of emission abatement reduced by GENCO$_1$, comparing with the case if it abates all of its required emissions by itself without trading.

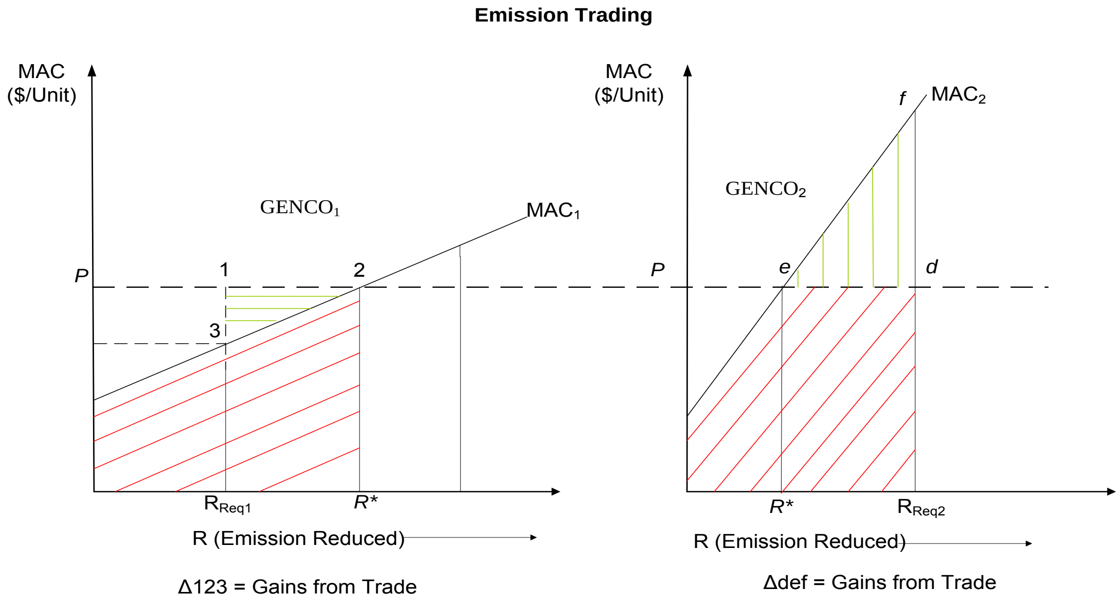

Fig. 2-4 Economic theory of emission trading scheme

On the basis of the economic theory of ET described above, the analysis is now extended to a mathematical model with a market with *I* companies. It is assumed that the beneficial function of the *i-th* company is:

$$\pi = p_i q_i - Pt_i - A_i[E_i(q_i) - t_i] - C_i(q_i) \tag{2-1}$$

where p_i is its price of the product; q_i is its product price; t_i is the amount of allowance trading; $E_i(q_i)$ is the emission function; $C_i(q_i)$ is the cost function; A_i is its abatement cost of emission; *P* is the market price of CO_2 allowances. Based on this assumption, the *i-th* company would compare its abatement cost A_i with the CO_2 allowances market price *P*. The company would sell a certain amount of allowance t_i when the market price is higher than its abatement cost, and visa versa. According to reference [60], each company would wish to determine the production according its marginal products so as to maximize their benefit. To maximize the benefit π, the behavior of the *i-th* company is described as:

$$\begin{aligned} & p_i^{'} - A_i^{'}[E_i(q_i) - t_i]E_i^{'}(q_i) - C_i^{'}(q_i) = 0 \\ & P - A_i^{'}[E_i(q_i) - t_i] = 0 \end{aligned} \tag{2-2}$$

If each individual Genco makes decisions based on sufficient information, the entire system will spontaneously achieve the socially optimum allocation of resources [70]. Theoretically, if all the emission trades could be excreted in a centralized manner, pollution reduction could be achieved in the most efficient way [63, 71, 72]. A well-defined international ETS enables countries to achieve ultimate global mitigation of emission. However, the above illustration neglects lots of realistic conditions, e.g. market power. Market power is the ability of a firm to profitably raise the market price of a goods or service over marginal cost. In perfectly competitive markets, market participants have no market power. A firm with market power can raise prices without losing its customers to competitors. Markets participants that have market power are therefore sometimes called "price makers," while those without are sometimes called "price takers." More detailed analysis should be conducted case by case although the feasibility of ETS has been theoretically proved.

2.3.2. The international situation of carbon markets

Climate change is a global problem that needs to be solved based on overall situation. A global solution can reduce the risks of dangerous climate change to acceptable levels, but it requires a comprehensive global agreement. However, this is a time consuming process and not easy to be achieved. It is climate change that weaves the multidisciplinary net connecting engineers, economists, environmentalists and policy enactors together to confront the climate change. In recent years, many public and government attentions have been paid on the subject of creating a well-defined ETS. This is because ETS is one of the most effective methods implemented in the above mentioned interactive areas. Several domestic and regional low-carbon initiatives, including market mechanisms, have been emerging in both developed and developing economies since 2005. Figure 2-5 summarizes the main regional, national and sub-national policy and market-based initiatives that currently exist to support global climate change efforts.

Fig. 2-5 International carbon markets

The booming of carbon market raises increasing concerns internationally. The value of the global carbon market climbed to a new high point in 2011, driven predominantly by a robust increase in transaction volumes. Just the total value of EU Emissions Trading Scheme (EUETS) in 2012 grew by 11% compared with the last year to US$176 billion (€126 billion). Furthermore, its transaction volumes reached a new high of 10.3 billion tons of carbon dioxide equivalent (CO_2e). However, the potential gains have not been fully exploited, because there are numerous obstacles and barriers which prevent the public sector, business and consumers from tapping into that potential. The World Bank estimates that carbon trading globally could be worth US$3.5 trillion by 2020, meaning that it would overtake oil to become the largest market in the world [16]. The electricity supply industry worldwide has been identified as a major source of greenhouse gas emissions. The power generation assets form part of the "combustion" installations which form the largest single sector in the world [17]. Therefore, further research focusing on the integration of CM with other markets is an urgent need to exploit the potential of its advantages.

EUETS is the backbone of the EU's climate policy and the engine of the global carbon market. It is also the world's largest carbon market. Australia will bring a nationwide cap-and-trade scheme by 2015 and is expected to cover roughly 60% of the country's annual GHG emissions [73]. Following Australia, New Zealand is considering linking with the Australian carbon market from 2015. In 2009, the Regional Greenhouse Gas Initiative (RGGI) was launched. It became the first mandatory ETS in the United States. It covers emissions from power plants in the Northeast and Mid-Atlantic States through to 2018 [74]. Besides RGGI, California's cap-and-trade program will be initiated in 2013. It is targeted for covering over 85% of California's annual emissions. Québec adopted its own cap-and-trade plan and is now working toward linking it with California's (within the context of the Western Climate Initiative) [73]. In early 2010, the Republic of Korea enacted the framework act on low carbon and green growth. At the same time, Japan launched the Tokyo cap-and-trade scheme as a local emission trading scheme. Currently the world pays particular attentions on China's carbon market development. According to China's advanced plan, it is expected to initiate several pilot cap-and-trade schemes to provide the foundation for a nationwide scheme in the coming years.

2.3.3. Research problems related to the implementation of ETS

It is climate change that weaves the multidisciplinary net connecting engineers, economists, environmentalists and policy enactors together to confront the climate change. In recent years, since ETS is one of the most effective methods implemented in the interactive areas, the striking developing of ETS has been concerned by increasing numbers from researchers, governments and public. Benefits from ETS have attracted much attentions of academics and professionals especially after the Kyoto Protocol has been enacted. Several problems related to the implementation of ETS are raised by a large number of researchers. The most concerned problems can be grouped into categories as follows:

A. Design of allocating allowances methods

According to Coase theorem [60], when trade in an externality is possible and there are no transaction costs, bargaining will lead to an efficient outcome regardless of the initial allocation of property rights. However, allowances allocation is one of most significant decisive factors affecting the overall performance of ETS in practice and also one of the most controversial challenges in the design of an ETS. Therefore, a large amount of literatures relating to allocation have emerged and various approaches have been developed to address the allocation problem. There are three categories of allocating allowances which can be distinguished from the economic point of view. The first one is exogenous criteria, which allows the entities receiving the permits with no additional cost. The other two are output-based allocation and auction [65, 75, 76].

The most common exogenous criteria are grandfathering (The allowances are allocated freely on the basis of a share of historical emissions) and benchmarking (emission allowances are granted on the basis of a proportion of historical production). All these methods can be applied in practice with little obstruction. This is because, instead of paying additionally, the entities have opportunities to gain more from the allocated allowances. However, this type of method has potential problems. For one thing, the new entrants need to buy allowances from existing entities. For another thing, entities may be reluctant to retire some of their old resources e.g. old plants with low efficiency because they can receive the allowances. These two problems may lead to some negative impacts on the electricity market planning and operation.

Output-based allocation does not require the entities to pay for the allowances. Entities would be allocated an amount of allowances proportional to their current production. Hence they have to reduce their own emission or buy allowances from the others. Either means would directly lead to a decrease in the GENCO's profits. One of the most commonly used methods in the power industry based on output-based allocation is Generation Performance Standard. The allowances are allocated freely to all generators according to their generation amounts in the year concerned. It is noticeable that some academics have confused output-based from benchmarking. The major difference between output-based allocation and benchmarking method is that the former allocates the allowances based on the emission per unit of electricity rather than the actual emissions. Therefore, all allowances are usually divided among sectors first so that each industry can allocate allowances based on their own indicators. In power sector, the indicators used can be in terms of "kg CO_2/ MWh" or "tonne CO_2/MWh".

When allowances are auctioned, they are allocated beginning from the highest bidders. Despite which kind of auction method is adopted, it is deemed as one of the best methods if its procedure is based on the non-discriminatory principle. The advantages of this method include providing fair competition for new entrants, revealing price signal of the allowances, and so on.

There are vast of studies advocating each path of allowance allocation. Without doubt, no methods can reach a consensus because different industries have their own features. L. H. Goulder and R. G. Cong et al. [77, 78] analysed the issues stemmed from EUETS's grandfathering allocation of allowance [65, 79]. They suggested that an auction path or a mix allocation method including auction can achieve global optimization from the economic point of view. Free allocation like grandfathering can be applied without significant obstacle while it would lower the entities' incentives of abating $CO_{2.}$ It is because the entities gain less free allowances in the short run if they increase the share of innovative technologies which produce less emission. Besides, grandfathering may create a bias against new firms entering product market, since existing firms get their permits free while new firms need to buy them. In the long-run, free allocation will tamper with competiveness. Output-based allocation does not discriminate new participants but it seems much like a subsidy to the product similar to credits. Besides, it may lead to an increase of public cost, which cannot be recovered from allocating and make the procedures much more complex [80]. Any case for free allocation to the domestic electricity sector must depend on income distribution, rather than economic considerations. A free allocation depending on income distribution is developed for preventing low-income households from experiencing disproportionate adverse impacts. An allocation based on economic consideration might lead to an increase of the allowance prices. This is essential to the success of a cap-and-trade program because the increase of the allowance prices would be the most important mechanism through which stakeholders would be encouraged to make economically motivated changes in investments and consumptions that would reduce CO_2 emissions. However, the increase of the allowance prices would be passed through cap-related costs to customers. This could have an adverse influence on the low-income households.

It is concluded that in the case of nationwide CO_2 regulation, the free allocation of emissions allowances could dramatically lead to overcompensation to the power industry as a whole. However, the impacts of free allocation method would be different when the method is applied to different parts of the industry. The benefit of auctioning is that the revenue from auctioning could be used to cut pre-existing taxes or to produce public goods, even increase welfare and employment. Besides, the auctioning will generate a market clearing price, which will provide a signal for price reference. It would seem intriguing to policy makers afraid of introducing auctioning because of competitiveness considerations or lobbying. Last but not least, from the insufficiency of EUETS's initially free allocation and the great success history of U.S. Acid Rain Act's auctioning, auctioning seems to be weighted much more than free allocation.

B. Cost-benefit analysis

Cost–benefit analysis is a systematic analysis of the expected balance of benefits and costs. Benefits and costs are expressed in monetary terms and are adjusted for the time value of money, so that all flows of benefits and all flows of project costs over time are expressed on a common basis in terms of their net present value [81]. P. M. Bernstein and M. Jaccard, et al. [71, 81] are the early economists who studied economical fundamentals stringently. Their researches indicate that ETS provides both cost benefit effectiveness and policy impartiality. Following their footprints, lots of individual or groups such as [82, 83] conducted different kinds of empirical analysis in U.S. to compare effectively the differences between ETS and traditional scheme of control. Accompanying with the novel evolving of renewable technologies, studies of investing Distributed Generations (DG) and other renewable energy sources (RES) via cost-benefit analysis were sweeping over. For instances, references [84, 85] explored how cost-benefit analysis and carbon accounting techniques are required by the Kyoto Protocol, the EUETS and other carbon trading mechanisms. Although there are versatile studies with different considerations of problems associated with ETS, a major concern on using cost-benefit analysis in environmental policies such as ETS is that the external cost is an uncertainty [86, 87]. Once there are chances that the uncertainties bring effects on the weighting of parameters, the validity of the model will be in doubt.

C. Research on market performance

Due to the technology development and environment protection, carbon markets and renewable markets have boomed simultaneously. Performance of the market operation has attracted lots of attention from academics in different research areas such as electricity society, market management and law enactor. R. W. Hahn studied the biases and inefficiencies associated with the use of either regulatory or incentive-based mechanisms [88, 89]. A. B. Jaffe et al. investigated the combined market failures of environmental pollution and innovation and diffusion of new technologies [90]. Investigating from another aspect of market performance, L. Mundaca and L. Chernyavs et al. focused their studies on the regulation and impact of the carbon market forces [91, 92]. It is believed that the imperfect competition in CM imposes adverse effects on both the household and commercial sectors. This is because the marginal abatement cost of CO_2 or other pollutants is expected to be fully or partially passed to the end-users. Most of them provide some alternative proposals on the market scheme, e.g. price control, permit issuance, avoiding trade distortion, etc. Besides, some researchers such as B. D. Solomon and N. R. Netusil et al. took the transactions cost into account in the operation of ETS [93, 94]. Plenty of similar studies on ETS proposed some revised alternative polices to improve the market performance. Besides the mandatory market, the voluntary market is a supplement to raise international concerns. Renewable Energy Credit (REC) is one of the famous voluntary markets. It is necessary to have these markets because they can benefit in developing alternative and sustainable energy source, increasing individual participations and completing the endogenous deficiencies of the mandatory one. O. Rousse et al. suggested that a benevolent regulator or non-governmental organization must correct certain CO_2 emissions market failures [95, 96]. L. A. Bird et al. considered that the two markets may have adverse impacts on each other [97]. Details of the impacts on mutual interactive markets will be given in the latter sections. As a conclusion, the systematic analysis from different considerations completes the fundamental basis of designing a suitable market structure with distinct backgrounds. Their contributions may shed lights on the successors who are interested in ETS. However, most of the policy suggestions or their conceptions of the market are lack of efficient verification process through modeling or mathematical analysis.

D. Investigation of the connection between carbon markets

The Kyoto Protocol specifies different goals for Annex I (or developed) and non-Annex I (or developing) countries. Most of the Annex I countries are now considering the international linkage with each other's carbon markets through different ways so that it may work out a global emission trading market ultimately [98]. Furthermore, the protocol sets out not only ETS but also joint implementation and clean development mechanisms. These enables the interconnection between Annex I and non-Annex I countries. In the international level, more than 50% of the global Certification Emission Reductions (CER) are provided by China, a non-Annex I country. And 80% of CER from China had been sold to EU-based entities. Linking between emissions markets without further restrictions always has some overlapping goals but the coverage may be different, e.g. different countries, different regions or different sectors. It is always suggested by academics that they need to have compatible market rules. From the prevalent literatures, the international connections can be classified into three distinct choices as follows [99-104]:

Linking international offsets: Such kinds of linking always exist between developed countries and developing countries via the offset program such as Clean Development Mechanism (CDM) which has already been introduced in chapter 1.

Direct or indirect market linking: Direct market linking exists between two carbon markets or in a carbon market recognizing international offsets as equivalent allowances. Market participants are therefore allowed to trade allowances with another carbon market or purchase international offsets from non-Annex I countries. The counterpart is traded through some other climate instruments such as CDM or voluntary market with other ETS markets.

Government or private linking: Government linking takes place when an international ETS plans to incorporate some countries which do not have carbon market itself. In this manner, some countries implementing different domestic climate policies can be linked up internationally. Besides trading through national gateways, private linking exists if two carbon markets are directly linked. The participants in different markets can trade directly. This is theoretically optimal but needs a sufficient legitimate status.

E. Impact of ETS on different industries

These studies considered issues from the viewpoint of different industries, e.g. firm, power generators and emission treatment plants. A.S.Malik [105, 106] investigated the noncompliance and cheating from firms which own market force. Further studies prove that deceiving behavior will emerge if the marginal abatement cost is higher than the cost of cheating or employing market force. Marginal abatement cost is the cost relating to the last and consequently the most expensive entity of CO_2 emission to be reduced, by which the price of CO_2 allowances for a period of time shall therefore be defined. Cost of cheating is the marginal penalty for cheating. Because limited budgets and prohibitive monitoring cost make complete enforcement impossible, noncompliance cases arise. Firms might cheat if the cost of cheating is less than marginal cost of compliance, which is the cost of obtaining an allowance for an additional unit of emissions. Therefore it is possibility, however, that firms may cheat and emit more than their stock of permits allows.

The number of similar analysis on industry behaviors affected by embedding ETS is vast. Existing literatures usually shed lights on the existence of the impact in addition to showing how far the impact would take place. Since the last decade, an inevitable tide of investigating uncertainties of ETS and its influences on the industry of other markets brought a mass of literatures. For instance, references [107-109] take uncertainty of CO_2 allowance price into account in the studies of some mature areas, e.g., bidding strategies, hedging arrangement and abatement option of EM. Introducing ETS into power system or energy market is a novel challenge since a lot of works have to be completed before it is comprehensively compatible with the market operation. Although still under the research and experimental stage, some efforts have been put into implementing ETS on different industries. More details of how ETS impacts on other markets will be given and compared in section 2.4 in this chapter.

2.3.4. Comparisons with other climate policies

Growing concerns about environmental issues have led to the establishment of several energy and environmental policies, of which the most relevant ones are those derived from the Kyoto Protocol [2] for the reduction of greenhouse gas emissions as well as those promoting renewable energies. Emissions trading scheme (ETS) was included in the protocol as a mechanism that could increase economic efficiency of the efforts to reduce greenhouse gas emissions.

There are three basic types of ETS: reduction credit programs, averaging programs and cap-and-trade programs [3]. A cap-and-trade program, inspiriting the implementation of the carbon market, is the focus of this thesis. Besides ETS, carbon tax [110] has raised several concerns as an alternative of ETS. To incite the use of renewable energy sources, renewable energy support schemes have been enacted in the power industry. This section will compare carbon trading with other climate polices. Fig. 2-6 presents the categories of the most important climate polices.

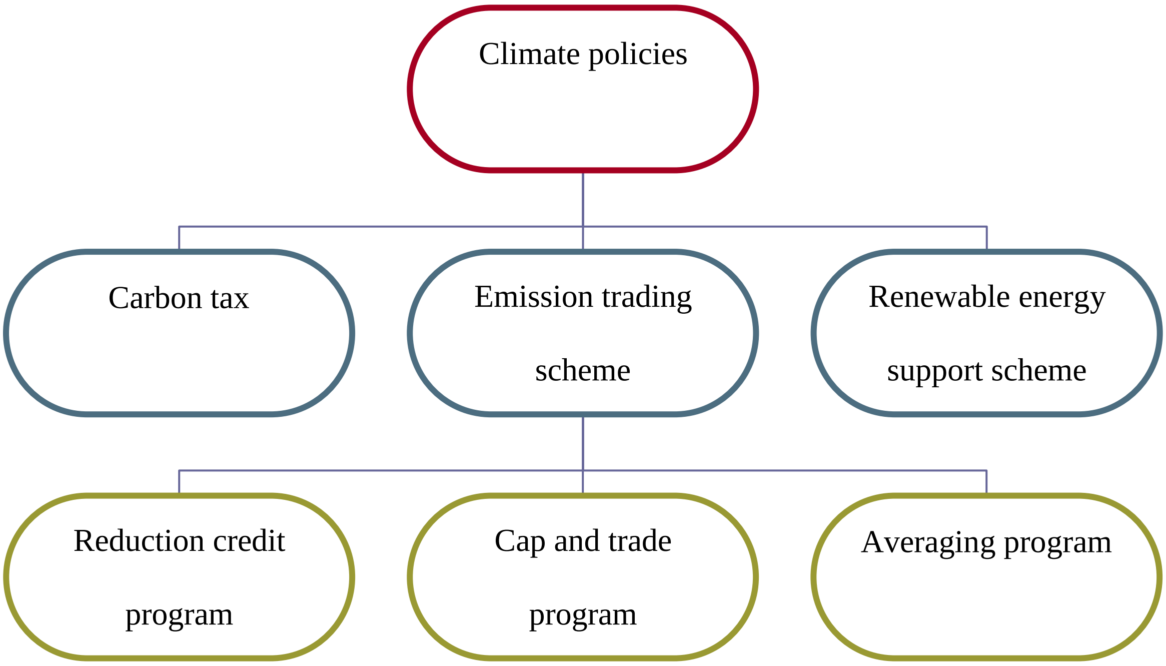

Fig. 2-6 Categories of climate policies

Cap and trade program, being the most widely adopted method of emission trading scheme, is the focus of this thesis. The performance of the Acid Rain Program [111] has proved that cap and trade is a successful method to control emission in large electric power systems. Under cap and trade program, each allowance represents an authorization to emit a specific quantity of a pollutant. All emission sources (i.e., GENCOs) are allocated a fixed number of allowances. They can decide the use of allowances freely but the total number of allowances is capped. In this manner, it enables the capped regions/ countries to reduce emission at the desired level. By the end of the compliance period, emission sources have to allocate sufficient allowances to cover their actual emissions during the period. The principle of the other two methods of emission trading schemes are similar to the cap and trade program, which is to provide sources with flexibilities to develop cost effective emission reduction strategies. Further details are given as follows:

A. Reduction credit program

In a reduction credit program, which is also referred to as a project-based program, emission sources are given credit for projects that reduce emission below a rated baseline during a certain period. K. G. Begg and S. Kartha et al. indicated that, to reduce emission to a same level, the cap and trade program could end up with a lower cost than a reduction credit program [112, 113]. Furthermore, reduction credit program has some disadvantages such as high uncertainty, high risk and additional cost related to the assessment of individual projects. Practically, mandatory market of ETS is always recommended in a cap and trade program form to ascertain the fulfillment of environmental goals. Whilst, reduction credit program has been proved a successful method in some voluntary markets [114]. Reduction credit program may include a larger variety of sectors and source types than that of the other types of trading programs.

B. Averaging program

Different from the cap and trade program, averaging program issues a performance standard with either constant or declining emission rate. It can be tons of emissions per megawatt hour for the electricity industry. Emission sources can sell the credits associated with average emission rates below the performance standard to other emission sources. This form of programs is considered to be the easiest one to be applied in different sectors simultaneously. This is because it can issue a specific performance standard in a sector having similar emission characteristics. It will be effective to promote efficiency if circumstances require a flexible cap on emissions.

Table 2-1 Comparison of the three approaches of emission trading scheme

	Potential to reduce emission	**Potential to minimize the cost**	**Costs related to administration & transaction**
Cap and Trade	High	Yes	Low
Reduction credit	Low	Yes	High
Averaging program	Medium	Yes	Medium

Table 2-1 compares the three approaches of emission trading scheme. It is noticed that the comparison is a kind of qualitative analysis rather than quantitative analysis which focuses on gathering of mainly verbal data rather than measurements. Gathered information is then analyzed in an interpretative manner. It can be concluded that cap and trade approach is considered to be the most widely adopted method with the highest potential to limit total emissions and have the lowest transaction costs. Any emission trading program should be designed for a specific region/ country with consideration of its pre-existing polices and situations.

C. Carbon tax

Although carbon tax has less support from lawmakers as it invokes the word “tax”, it is considered to be an efficient climate policy by some academics and advocates. A marked difference between carbon tax and cap and trade is that the former set the price of CO_2. Cap and trade allows the market supply and demand of emissions allowances determine what their price will be. In the acid rain program, there was a time that the price of allowances rose from US$80 to US$200 per ton. It was due to a tightening of supply and the revision in the program rules [115, 116]. In the EUETS [117], the price of CO_2 allowances has fluctuated more dramatically, from 20 Euros to less than 1 Euro per ton in phase I (year 2005-2008) [118, 119] .

On the contrary, carbon tax is determined by the government so that it allows entities to affect the total emission level. Since the cost of emission is fixed, the economic costs of implementing a new climate policy can be controlled to a reasonable extent. A fixed carbon tax actually offers a simpler and easier mechanism for ensuring cost certainty. To avoid the cost effect, carbon tax is especially suitable for developing countries that are undergoing economical revolution. When novel techniques that can tackle the problems relating to climate change are available, establishing a standard to support the techniques is a better way to institute a cap and trade program. However, low-cost means to remove CO_2 from combustion process and devices for reducing the effects of CO_2 are not available at the moment. Thus, an alternative method is needed to incite the CO_2 abatement. The virtue of cap and trade is to inspire both the demand side and the supply side to fulfil their emission reduction in the financial markets. CO_2 emissions produced by generators are regarded as negative externalities. This is because generators’ productions impose negative external costs to the atmosphere which is a common property resource.

Either carbon tax or cap and trade could internalize the negative externalities. Carbon tax is a charge on each unit of a firm's emissions. An emission fee will cause the firm to reduce its emissions to a level at which the marginal cost of abatement equals the imposed emission fee. Therefore, the negative external costs are internalized to each firm through taxes.

As explained in Fig. 2-4, if there are enough firms and permits, a competitive market for the allowances will be developed through cap and trade. In market equilibrium, the price of an allowance equals the marginal cost of abatement for all firms. Firms with relatively low marginal abatement costs will have larger emissions reduction, while those firms with relatively high marginal abatement costs will buy more allowances and have smaller emissions reduction. Each firm or country will strive to balance the cost of abatement against the price of buying or selling allowances. Therefore, the marginal abatement cost for all firms will be lowered through market competition. Compared with carbon tax, cap and trade can internalize the externality of emission reduction in a way that the carbon tax could not provide. In cap and trade programs, the companies have incentive since the performance in deciding CO2 abatement and behaviour in carbon market will finally turn out to be a decisive factor to their revenue.

D. Renewable energy support scheme (RESS)

The objective of the implementation of RESS is to promote the rapid development of the renewable energy sources. RESS has traditionally been based on three main mechanisms: fixed-price systems, fix-quantity systems and bidding systems, which are presented in Fig. 2-7. There are four general methods under fixed price systems: investment subsidies, fixed feed-in tariffs, fixed premium systems and surcharge-funded. Investment subsidies are given to investors based on the rated power. It has caused problems that some large wind farms received the subsidies while actually produced little power.

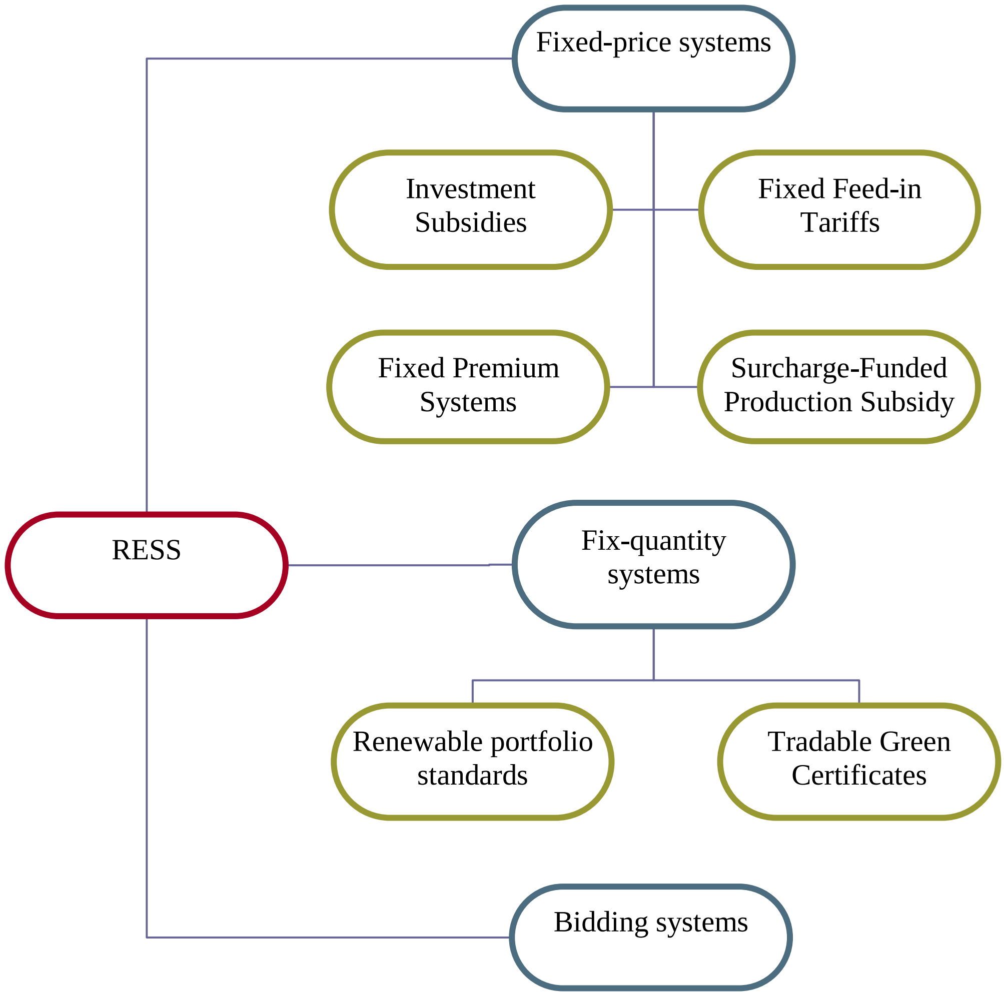

Fig. 2-7 Categories of RESS

The difference between feed-in tariffs and fixed premium system is that the total electricity price received in the former is fixed while in the latter is volatile. Fixed feed-in tariffs are relatively straightforward to encourage forward planning and stimulate the usage of renewable. A fixed price per kWh electricity is paid to the operator when the renewable energy is fed into the grid. Similar to feed-in tariffs, fixed premium system requires a fixed rate to be added to the electricity price. Therefore, the fixed premium system is less predictable for a GENCO because its revenue depends on the fluctuated electricity prices. It will reflect the external costs of conventional power units. Different from the previous methods, surcharge-funded are paid by consumers for all electricity purchases. Renewable generators are paid for each kWh unit of electricity produced from the revenue of the surcharge. Among the four introduced methods, fixed feed-in tariffs are most widely applied to support renewable sources in power system.

Fix-quantity systems have two variations: Renewable portfolio standard (RPS) and tradable green certificates. RPS requires electricity generation entities to produce or purchase a certain percentage of their electricity from renewable energy sources by a specified date. RPS regulates the quantity on the generation side while tradable green certificates apply on the consumer side. Tradable green certificates require retailers to purchase a certain amount of certificates. They are subject to a penalty when there is any shortfall of the pre-determined amount. These two methods have been applied in nearly half of the states in almost all regions of the USA [120]. However, renewable markets are driven by different states individually because different states have their own preferences for renewable.

Bidding System removes political risk for the investors of renewable energy. Power suppliers are allowed to bid for supplying a limited wind energy capacity in a given period for a given price.

Although renewable energy support scheme (RESS) is to promote the use of renewable energy sources, it is obviously that RESS and ETS have overlapping goals with respect to the global environmental and economical benefits. Under RESS, the development of renewable energy sources are usually supported or inspired by governments and generally can obtain priority and subsidy to generate electricity. This may reduce the demand of traditional thermal generation electricity technologies and further reduce CO_2 emissions. Given this background, with the implementation of these two schemes, the impacts of these two schemes on operating electricity markets are examined in chapter 6 and chapter 7.

2.4. Analysis of Interactions Among Electricity Market, Carbon Market, Fuel Market and Renewable Market

Emission trading scheme, which is one of the main focuses in this thesis, is a key mechanism playing a significant role to link the four interactive markets including electricity market, carbon market, fuel market and renewable market. This section will conduct a comprehensive analysis and shed some lights on the impact of ETS on each market.

2.4.1. Impacts of emission trading on electricity market

A. Impacts on electricity price

The supply and demand of emission allowances determine the price in carbon market and the price fluctuates over times. The fluctuation of the carbon price will shift the related cost to end users through the whole supply chain of electricity production. It is expected that this influence will be derived directly from the level and period of carbon emission constraints and also the carbon intensity of the relevant supply chain of the industry (i.e., transmission and distribution). The most explicit observed consequence is that electricity prices are affected. All GENCOs are expected to shift the incremental cost of emission allowances or even higher cost to their end users. However, the eventual impact of carbon price on the electricity price is non-stationary. This is because the eventual impact might be affected partly by the transmission and distribution cost. Whist, the impact can be discussed through two continued but different stages (wholesale stage and retail stage) as follows:

- The impacts on wholesale prices

Lots of literatures studied different environmental policies and their impacts on electricity wholesale price. P. del Río González incorporated several environmental instruments to analysis the impact of ETS on the electricity market via electricity demand and price fluctuation [121]. In this study, impacts are analyzed via two regions (A and B) under four scenarios considering different market structures and policies: (1) National environmental-energy policy and national electricity market; (2) International environmental-energy policy and national electricity market; (3) National environmental-energy policy and International electricity market; (4) International environmental-energy policy and international electricity market.

Table 2-2. Effect to electricity price under four scenarios

	Wholesale Electricity Price		**Electricity Demand**		**Costs for the Consumers**	
Region	**A**	**B**	**A**	**B**	**A**	**B**
Scenario 1	↑	=	↓	=	↑	=
Scenario 2	↑(A)>(B)	↑(A)>(B)	↑(A)>(B)	↑(A)>(B)	↑(A)>(B)	↑(A)>(B)
Scenario 3	↑	↑	↓	↓	↑	↑
Scenario 4	↑	↑	↓	↓	↑(A)>(B)	↑(A)>(B)

It can be observed from Table 2-2 that electricity demand in scenarios 1, 2 and 4 are not promoted. The comparative static analysis of the impacts of ETS on the two regions is based on a graphical approach. However, the wholesale electricity prices are expected to be increased in almost all scenarios. This proved that the conjecturing of a GENCO is expected to shift the incremental cost of emission allowances or even higher cost to the end users as mentioned in the last paragraph. This work provides analysis from the macroeconomic aspects but does not consider the dynamic effects of emission trading on GENCOs' operation.

In the light of the theoretical fundamentals, different kinds of simulation models have been developed to investigate the impacts of ETS on the wholesale electricity price. In Netherlands, the total cost of generating electricity is demonstrated to be increased by around €430 million [122]. Equivalently, the average electricity wholesale price is expected to be raised by 0.41€ cent/kWh. A fundamental electricity market model named VTT is proposed in [117] to study the electricity price variation due to the implementation of the EUTES. The VTT model is based on physical demand and production of electricity in a market area, i.e. the Nordic Countries, and the trade between neighboring regions such as Russia and Central Europe. The result indicated that the annual average wholesale price was increased by €0.74/MW for every €1/t CO_2 in the Nordic area. However, these studies considered that the price of emission allowances is fixed at €10/t CO_2.

Besides the quantitative analysis, several competitive models have been developed to provide qualitative analysis of the wholesale electricity price variation due to the introduction of ETS. For example, L. Chernyavs'ka and F. Gull [92] examined GENCOs' behavior in the electricity market when implementing ETS. It is concluded that the incremental cost of GENCOs will be passed through to the customers via the increase in electricity wholesale prices. The investigations made in this study are based on an Italian market. The qualitative analysis shows that an increase in the wholesale price is incurred in the short term. The increase in the wholesale prices is mainly because it internalizes the marginal opportunity cost of carbon allowances. These studies can characterize the impact of carbon trading on the wholesale price clearing in the short-run. It has been demonstrated that, with ETS, the electricity market structure is a direct determinant to the increase in the wholesale price.

While market factors will cause influences on electricity price, some non-market factors will also affect the EM. R. Kannan and H. Winkler et al. adopted the MARKAL model, a least-cost optimizing tool, to analyze the impact of different energy policies [123, 124]. R. Kannan [123] set the emission reduction target at 60% reduction in CO_2 emissions at national level by 2050 as UK government did in 2000. Various parameters such as energy costs, plant costs, plant performances, building performance and so on, were inputted and the model chose an optimal technology mix to meet that demand at minimum cost. Based on the least cost optimization linear programming, the MARKAL model minimizes the total discounted energy system cost by choosing the investment and operation levels of all the interconnected system elements. The problem is optimally solved from year 2000 to year 2070 in 5-year increments. MARKAL is a generic model tailored by the input data to represent the evolution over a period of usually 40 to 50 years of a specific energy system at the national, regional, state or province, or community level. The majority of the literature on modeling studies has generally focused on modeling without taking policy influences into account. MARKAL model is recommended to be adopted while sometimes the policy impact is so significant that cannot be neglected. It can be concluded from vast of literatures mentioned in this chapter that the implementation of ETS leads to an increase of the electricity wholesale price in the short run. Several most important factors that determine the increase rate of the electricity prices are summarized as follows:

Factors from CM:

1. The interconnection of region/ nation carbon markets or other region/ nation climate policies e.g. carbon tax.

2. The initial allocation method in CM and the competition intensity. It is mainly affected by the regulator or politicians' risk attitude towards the high price.
3. Current price levels in CM. If the prices are at a relatively high level, it will lead to a negative influence on the new entrants.
4. Current and the fluctuation level in CM. If the prices are fluctuated at a relatively high level, the market participants will be inclined to seek for profits in CM rather than only in EM. This will alleviate the increase rate of the electricity prices.

Factors from EM:

1. Other EMs can be connected. The connected EMs can be operated in different market structures or can have different environmental policies. The carbon intensity of the supply chain of the new connected electricity industry includes the generation, transmission and distribution is a key factor of electricity wholesale prices variation when employing ETS.
2. The average rate that GENCOs shift their incremental cost related to ETS to the customers is one of the determinants of electricity wholesale prices variation.
3. Market power of some GENCOs in the EM will affect the wholesale price in another way. A GENCO which has market power can adjust its supplies due to the incremental cost of reducing emissions. Because the network constraints limit the transmission freely, to avoid congestion of transmission, the wholesale price may have no option but to be increased.

- The impacts on retail prices

Similar to the wholesale price, the retail price cannot be exempted from increasing. However, several alleviate methods could be imposed to induce the electricity market passes less of the incremental cost of reducing emissions to the customers. ETS affects the electricity retail price in many ways, of which the most important factors are the carbon market environment and the applied policy. Furthermore, other related sectors covered by ETS may affect the electricity retail prices. Different market structures in CM (i.e., different methods of initial allowances allocating, the covering sectors and commitment periods) and EM lead to the significant variation in incremental retail price [122]. Recently, B.Cheze and J. Chevallier found that carbon price changes respond not only to retail prices forecast errors but also to industrial production in the other two sectors (i.e., paper and iron) covered by the EUETS [125]: combustion and iron. Reference [126] analyzed the interplay between daily carbon, electricity and gas price data with the EUETS for CO_2 emissions. A. Sadegheih conducted a survey in [127], which has concluded from vast of literatures mentioned in [128-131] that the implementation of ETS leads to an increase in the electricity retail price. Several most important factors determine the increase rate of the electricity prices are summarized below:

Factors from CM:

1. Current price levels and the market structure in CM;
2. The interconnection of other EMs with or without different structures or environmental policies;
3. The level of carbon cap and the production in other sectors covered by the ETS.

Factors from EM:

1) Market structure and carbon intensity in EM;
2) The price elasticity of demand in EM;
3) The type of the long term electricity contract in EM;
4) The market power of GENCOs;
5) The incremental cost of available technologies which GENCOs can adopt to mitigate or avoid increasing the carbon emission.

B. The Impacts on Generation Investment

The fluctuation of the prices in CM is an incentive for a GENCO to seek for profits in CM. For either short term or long term planning, GENCOs have motivations to make investments. The carbon intensity across the current supply mix will vary significantly, which will cause enormous variations in the relative short run marginal cost (SRMC) of the generators [10]. Although generators will therefore benefit from a rise in price, the ones who have relatively lower emission and renewables have predominant advantages in the electricity market planning and operation. Therefore, for short term (usually less than ten years), investment may be placed in technologies which can reduce the carbon intensity. For long term (usually more than fifteen years), without doubt, investment in exploiting renewable sources is a trend. However, for both short term and long term, the impact on generation's investment will fluctuate considerably. Basically, ETS will affect dispatching arrangement in short term and lead to the investing plan in the long run. In this manner, the impact can be discussed through two continued but different stages (short term investment and long term investment) as follows:

- The Impacts on Short Term Investment

It can be concluded from a large number of literatures including [10, 132, 133] and the others mentioned in this chapter that the investments in short term are affected significantly by the uncertainties from the prices level in CM, policy guidance and market structure. Substantial returns in CM lead to variations in either demand or supply side of electricity industry [134]. From demand side, the price elasticity varies and sometimes consumers prefer to purchase less electricity. As mentioned in part A of this section, F. P. del Río González indicated in [121] that the interconnection of markets with different structures will lead to different demand responses in EM. From the supply side, GENCOs are expected to have their own decision makings. Economic dispatch merit order, usage of fuels and also the trading of carbon allowances are adjusted based on the fluctuation of the carbon prices. To confront these changes, GENCOS are expected to invest in several technologies.

According to [135], several studies had investigated the short term investment due to the implementation of ETS. It is shown that when the price of carbon price is around €18.5/t $CO_{2,}$ the major electricity supply will be switched from the traditional coal plant to the combined cycle gas turbine (CCGT). The investment on CCGT will lower the emission of CO_2 by a half. Besides CCGT, gas turbine is another alternative for GENCOs to invest. The switch from coal to gas generation is highly dependent on the gas prices in FM. If the carbon price is stable at a relatively high level and the gas prices in FM are relatively low, gas generations are without doubt superior in dispatching order. The concerns of GENCOs in EUETS are investigated in [10] and it is concluded that GENCO would include the cost of allowance and the abatement cost when they make decision on investment. A dynamic decision making model is developed for a GENCO under the ETS [136]. The proposed model illustrates how different levels of emission allowance affect a GENCO's behavior and total profits. A GENCO needs to consider its own production and dispatch of each unit in the most economical way. However, this study has not considered the impacts from FM. The deregulation of EM and the implementation of CM require each GENCO to build up its own fuel portfolio according to the prices variation in FM. Therefore, to take the uncertainties of electricity market, carbon market and fuel market into account, a novel two-stage stochastic optimization decision making model to deal with the multimarket trading problems in each trading interval is developed in chapter 5. Usually, the industry does not want high investing risk when planning the carbon investments. Taking into account of the risks and uncertainties of the prospect of CM, the industry would prefer to embrace some low carbon investments, such as short term investments to improve the energy efficiency in the existing power plants.

The most probable investment plans in short term are summarized as follows:

1. Reducing the production in high emission generators;
2. Investment in allowances from CM; The fluctuation of carbon prices is an incentive for some firms to seek for profits in CM. Some firms might decide to purchase or invest in some programs in order to obtain certain amounts of carbon allowances, by which they have the chance to sell the allowances when the market price is high enough to make a profit.
3. Investment in energy efficiency projects in the existing plants;
4. Revision on the generation scheduling merit order. Base load from the traditional coal generators will be shifted to existing gas generators or else with relative lower carbon emission.

- The Impacts on Long Term Investment

Different from short term investment that confronts lots of uncertainties, most GENCOs would include the effects of implementing ETS in their long term investment. Technologies with lower emission intensity which are economically available attract GENCOs' investing interest. The future cap of emission level and the price in CM are the major factors to determine which kind of lower emission technologies are predominant in electricity supply. The market prospect and a GENCO's attitude will finally determine which kind of lower emission technologies will be adopted. It is concluded in [133] that GENCOs will sometimes be incented to invest in lower carbon technologies to switch the ones with higher but rational carbon emissions.

ETS has been proved to become an increasing important role in affecting a GENCO's investment decision making. In Finland, a GENCO's long term planning is determined mainly by the price of the allowances. The allocated allowances and the maximum possible allowances that a GENCO could acquire can also contribute to the decision making [72]. The quantitative statistical study showed that the carbon price's volatility and correlation of with prices in EM and CM contribute to the decision making of long term investment. In [137], X. Q. Ji proposed a method combining the real options approach and the least square method (LSM) to evaluate investment opportunities due to various uncertainties existing in generation investment planning. A conclusion has been drawn from the case study of the thermal power plants that the decision making of long term investment are affected significantly by the uncertainty relating to the allocation method of emission allowances.

When making decision on long term planning, especially investing in a new generation plant, GENCOs are confronted with problems of lacking long term information. The duration span of a new generation plant is usually 20 -30 years. However, ETS market operation is always affected by the international negotiations. GENCOs therefore are subject to limited information and uncertainties of the market prospect when they made decision on investment. They have no choice but confronted with lots of uncertainties. On one hand, this might lead to a negative influence on the investment in the power industry as a whole. On the other hand, this might increase the competiveness and the diversity of the electricity market operation because more choices of technologies are available for the new entrants. To avoid increasingly uncertainties in the long term investment, a long term ETS policy is of impotence and can stimulate the investment in different novel technologies [133, 138, 139].

The implementation of ETS has significant influences on GENCOs' operation. On one hand, GENCOs are stimulated to develop cost effective emission reduction strategies. On the other hand, they are subjected not only to physical constraints in EM but also environmental constraints in CM. One significant change is that some generators which lose their cost advantages in EM might have chances to earn the superiority in CM. It is possible that some generators decide to reduce their individual emission lower than the required level. They can then sell the surplus allowances to other generators or entities that confront higher abatement costs. In terms of replacing existing generators, technologies such as wind power, geothermal and carbon capture and storage become increasingly competitive when the prices in CM rise. For some generators with relatively high carbon emission factor, when the prices in CM are high, plant retirement become an economical decision although their SRMC might still be competitive in short run. Due to economical reasons, most countries implementing ETS have not established special policy for cases of new entrants and plant retirement. Whilst, different allowances allocation approaches are employed to encourage the retirement of generators with high emissions so that new entrances can get a space. To maximize the expected profits in the long run, the following choices are available for a GENCO:

1. Investment in replacing alternative or cleaner fuels;
2. Coal-fired units are progressively substituted by CCGT or other low carbon emission units;
3. Investment in emission control technologies and instruments;
4. Investment in wind power, geothermal, carbon capture and storage;
5. Retire.

2.4.2. Impacts of emission trading on carbon market

As mentioned in section 2.3, CM is a market which operates on the basis of ETS. As far as climate issues are concerned, EM, RM and the related secondary markets of CM have overlapping goals. Secondary markets of CM include forward transactions, option transactions and over the counter market. Market participants are expected to optimize their planning and operation in these interconnected markets simultaneously. Therefore, ETS will react on the CO_2 allowances price in CM via the participants' responses to the co-existence markets.

In a well-defined CM, the implementation of ETS will lead to a relatively high carbon price level. Thus the price in CM can affect RM positively. On the other hand, a mandatory RM will affect the dynamics of CM, with the potential of lowering the price level in CM. This interaction may ultimately lead to a structural change across the covered sectors. Power industry, possessing the overwhelming majority of CO_2 allowances, is a big party in participating CM and thereby GENCOs' attitudes and performances will be the major determinants of allowance prices.

Secondary markets of CM are similar to the existing ones related to current EM, FM and RM. It can benefit the stability of CM and enables participants in the market to make the tradeoff between their own risk and opportunity. E. Benz and J. Seifert et al. study the dynamics of allowance price and seek to find out the price determinants in [140, 141]. Since the first CM in scale or scope only came into effect from 2005, thus each of the numerical study was based on data from EUETS. Factors from other markets will affect the forecasting allowance price, such as energy prices in EM, fuel prices in FM. Besides, the sub-period decomposition of the pilot phase gives a better grasp of institutional and market events that drive changes in allowance price. Recent results from [125] showed that carbon price changes respond not only to energy prices forecast errors and extreme temperature events, but also to industrial production in two sectors covered by the EUETS: combustion and iron. [140] developed a price model that dealt with volatile price processes induced by short term factors such as the spread between fuel prices, precipitation, summer and winter temperatures and the setup of a trading environment. The literature also pointed out that the demand and the value of a stock is based on profit expectations of the underlying firm. The CO_2 allowance price is determined directly by the expected market scarcity induced by the current demand and supply in the CM. From this literature, price determinants of CO_2 emission allowances are: 1. policy and regulatory issues; 2. market fundamentals of CM; 3. Production of CO_2; 4. Demand and supply of CO_2 allowances.

Studying the dynamics of allowance spot price is an interesting topic. Attentions should also be paid to the derivatives of carbon like futures and options in secondary CM. The nature of carbon price has no difference when comparing with other commodities but it is affected by factors from other interactive markets such as EM, RM and FM.

2.4.3. Impacts of emission trading on fuel market

Following the deregulation in electricity market, several naturally interrelated fuel markets such as coal, oil and natural gas markets [4, 5] are developing to more competitive environments. Nowadays electricity demand is growing significantly, the fossil fuels are being increasingly scarce. Moreover, the climate change impacts are gaining more and more attentions. All these phenomena motivate a shift towards less CO_2-intensive power supply technologies. The implementation of emission trading scheme provides economical incentives for GENCOs to switch a substantial fraction of power capacity from fossil fuels to renewable technologies such as geothermal, biomass, or wind-powered turbines. These changes have significant effects on GENCOs' management of their own fuel portfolios. The changes lead to a variation in the demand of closely related fuel markets such as coal, oil and natural gas market.

The substantial development of shale gas in recent years serves as a good example of the positive impact of ETS on the fuel market. Shale gas is natural gas which is trapped within shale, a type of fine-grained sedimentary rock. With both economic benefit and environmental benefit, shale gas provides an important alternative for either countries or companies to meet their GHGs emission targets. In 2012, The US CO_2 emissions dropped to a 20-year lowest with the help of the rapid shale gas development [73]. Shale gas contributed to over 20% of U.S. natural gas production in 2010 while the number is only 1% by 2010. With abundant shale gas deposits discovered and even more new potentials spots, shale gas seems to have chances to greatly expand around the world, especially in power industry. Because gas is relatively cleaner than coal and oil, GENCOs' fuel portfolios are expected to switch to shale gas in respond to their CO_2 reduction targets. The proportion of natural gas in power industry's energy mix could rise in the short term. However, unless technological advances make carbon capture and sequestration techniques more effective, GENCOs are expected to be less depende on all fossil fuels, including shale gas. In the long term, the implementation of ETS will therefore leads to the expansion of renewable energy gradually.

The shale gas has been sensational in US as its revolution made gas cheap again and developed extensively. Among all fossil fuels, shale gas is considered cleanest as it emits lower level of either CO_2 or SO_2 emission. Therefore, GENCOs who are under cap and trade problem or other polices may switch to this more efficient fuel. Besides, shale gas, as a new source having great potential, could help to keep the OPEC (Organization of Petroleum Exporting Countries) from being monopoly on fuel prices.

Shale gas is either potentially lucrative or hazardous. Some states in USA has exploiting it while others has banned it because of its high risk in water contamination due to leakage. From the environmental aspects, the requirement of large quantities of water for fracturing might result in shortage of water in some areas. Besides, the fracturing liquid or fluid, which contains hazardous chemicals, might pollute the surrounding if it is not well controlled. Last but not least, the water that has been used, which contain dissolved chemicals, in the fracturing processes has to be treated before its reuse.

A. Rentizelas et al. [142] investigated the probable effects of various scenarios for emission allowance price evolution on the future electricity generation mix in Greece. The RPS targets are included in the long term analysis to determine the optimal generating mix to minimize electricity generation cost, while satisfying system constraints and incorporating the uncertainty of emission allowance prices. Besides increasing the usages of renewable sources and reducing the adverse environmental impacts, ETS will reduce the power industry's dependence on fossil fuels. From economic theory, it is of importance to diversify the supplying sources so as to achieve competiveness in a market. This can improve the market performance in either electricity market or fuel market because the prices on the two markets have strong dependencies and correlated interactively. J. W. Mjelde and D. A. Bessler [8] implied that price determination is more likely to be in the hands of the market participants than in the regulators' hands. Having market participants determining price may allow participants respond more quickly to changes in major fuel prices. Specifically, electricity spot markets may respond to price changes in its major fuel source markets (i.e., coal, oil and nature gas markets).

The deregulation of EM and the implementation of CM require each GENCO builds up its own fuel portfolio according to the price variation in fuel market. In the long run, GENCOs therefore have to contract their fuels in an optimal way that allows them to operate in the multimarket environment without incurring any negative profits. In the daily operation, with consideration of different fuel prices, GENCOs have to decide the usage of their fuel according to the production. As fuel cost is still the major factor affecting GENCOs' decision making, GENCOs will decide to adopt a suitable mitigation method, with the prices in regional/ national fuel markets taken into account. R. Sims et al. concluded several methods for mitigation of CO_2 emission in [143]:

A. Increasing the efficiency of fossil fuels

On one hand, the current average energy efficiency in power station is at a relatively low level of around 30%. Based on the analysis through the MARKAL-Macro energy system model by setting the overall emission reduction target to 60% reduction in CO_2 emissions at national level by 2050 as UK government did in 2000, the power industry shows the potential to increase the emission reduction by 30% higher in the long term by technological development. On the other hand, the utilization effectiveness of fuel can be enhanced by using cogeneration plants. N. Strachan [144] indicated that the combined heat and power (CHP) offer both reduced costs and significant reductions of CO_2 emission. A successful example in Europe showed CHP's ability to use the waste heat from electricity generation, raising total system efficiencies up to 90% (higher heating value (HHV)) in the best applications [145].

B. Switching to low-carbon fossil fuels

Some countries are undergoing reform in some specific fuel markets, coupled with the electricity market. In this case, the investment decision makers in the electricity supply industry would lead to a switch to low-carbon fossil fuel from coal. For example, motivated by the rapid development of the natural gas fuel market, the Combined Cycle Gas Turbine (CCGTs) allows GENCOs in Australia to use high efficiency, low capital cost technique to reduce carbon emissions [146].

C. Decarbonising of fuels

Decarburization of fossil fuel can become an effective GHG abatement option. This process can be adopted either before combustion or after combustion. In both cases carbon dioxide can then be stored over geological time frames, for example, in depleted gas fields.

D. Increasing the use of nuclear power

Nuclear energy could replace base load fossil fuel electricity generation in many parts of the world if acceptable responses can be found to concerns over reactor safety, radioactive waste transport, waste disposal and proliferation.

E. Increasing the use of renewable sources of energy

Technological advances offer new opportunities and declining costs for renewable energy technologies which, in the longer term, could meet a greater share of the rapidly growing world energy demand.

To gain a better understanding of how a GENCO would react to EM, CM and FM, the impacts of carbon policies with the interactive markets on the decision making of a GENCO is analyzed in chapter 5. To take the uncertainties of electricity market, carbon market and fuel market into account, a two-stage stochastic optimization model which provides the optimal results in both production process and trading process is developed.

2.4.4. Impacts of emission trading on renewable market

Over the past decade, mandatory renewable targets have expanded significantly worldwide. As introduced in Section 2.3.4, RPS, one of the largest drivers for new renewable energy generation in U.S., has been introduced in chapter 1. However, the implication on renewable energy generation sources might be slightly different with the co-existence of ETS.

The implementation of ETS can benefit the operation in RM. This is because ETS can lead to credible transactions with price signal in either CM or RM. A reasonable price level is of importance to drive structural changes in energy society. Similar to CM, price fluctuation in RM motivate investors, electricity producers and consumers to diversify the power sources. Both electricity production and consumption are progressively reached to the ultimate optimization. RM, coupled with ETS, is expected to compel the market participants to exploit renewable sources so as to achieve a fixed quantum of renewable penetration in the energy industry. To confront the uncertainties in either renewable technology or market, it is possible to replace the non-renewable technologies with the alternatives which contribute lower emission in both short term and long term. Besides economic consideration, displacing parts of the fossil fuels generators with renewable generators such as wind, solar, hydro, biomass and geothermal units can reduce carbon emission significantly in energy industry. However, the cost for establishing and operating renewable generations is a bit higher than its counterpart. Thus, S. E. Fleten et al. explored a method for evaluating investments, under allowance price uncertainty, to maximize the profits from the investing opportunity [147]. Results indicated that the intensity of price volatility affects RM's performance significantly. High price volatility increases the value of the investment opportunity and therefore makes it more attractive to postpone investment until larger units are profitable. According to reference [147], the optimal investment strategies in decentralized renewable power generation depend on several factors including electricity load, climatic data and electricity prices. With the analysis using the data provided by the Nord Pool, the optimal strategy is investing in different capacities at different price ranges. Furthermore, the analysis shows that increased price volatility increases the investment price thresholds, and can increase the value of the investment opportunity for larger projects so much that the only optimal strategy is to wait until investment in the largest project is optimal.

As introduced in Section 2.3.4, there are several methods of RESS which have been implemented in order to promote the development of renewable energy sources. A support system for electricity from renewable energy sources, RES-E, has been developed in Europe [148]. It is expected that RES-E would serve as an international label of renewable energy sources. The policy option for increasing the RES-E penetration in Greece has been evaluated in [149]. When the increasing rate of the RES-E penetration is larger than that of energy demand, renewable units are expected to displace the fossil fuel units in scale. The direct result of the promotion of renewable sources is the reduction of carbon emission. This leads to the decrease in the demand of carbon allowance so that the price in CM is expected to drop. It is shown that, in the first phase of EUETS, an additional RES-E had led to the retail electricity price decrease to as low as €2.6 /MWh. Besides, a market-based cost-efficient framework based on tradable green certificates (TGCs) was developed for electricity production from renewable energy sources. TGCs are the most widespread RESS in Europe together with feed-in tariffs, which can be easily coupled with EUETS [150]. However, a specific RESS like TGCs would result in a higher renewable energy for consumers if it was directly promoted without ETS. It is concluded in [151] that the impact of ETS on RM is significant only when the carbon prices are very high. Furthermore, the increase in renewable energy sources deployment would be achieved at a higher cost because the incremental cost is expected to be passed to end-users.

Using a simple model and traditional optimization solution method, Jensen and Skytte concluded in [152] that the implementation of a RESS can result in electricity prices declining. This is because the renewable part of electricity supplies is subsidized by the RESS. Although the electricity price is decreased, consumers suffered the incremental cost relating to the related policies. For example, they are asked to pay addition cost for the use of renewable energy sources. They find that it is ambiguous whether the additional cost would be higher than the saving cost. Therefore the net consumer costs can either increase or decrease as a result of the introduction of an RESS [20]. Rathmann specifies that the introduction of RESS affect either the price of electricity or the renewable energy prices. With a national RESS in the years 2005-2007, the wholesale price of electricity are reduced by 6.4 €/MWh, whilst the renewable energy sources fee are increased by 3.8 €/MWh in Germany [153]. The simulation showed that the retail price of electricity would be, comparing with the without RESS case, 2.6 €/MWh higher.

The implementation of ETS and RESS would bring many new problems to electricity market operation. The impacts of these two schemes on the profit of different types of generation companies are obviously different. Also the market shares, outputs and operation strategies of generation companies may be changed and moreover the operation of the whole electricity market would be affected. Thus, it is necessary to conduct more researches on this subject. Reference [20] investigated the impacts of ETS and RESS on the electricity market operation. Simulation results show that CO_2 emission reduction can be sustainable and the energy sources structure in the future can be optimized. Further details of this study will be discussed in chapter 6 and chapter 7.

Among all renewable technologies, wind power is the most important one for the electricity industry. It has attracted much attention and become a hot topic in electrical power engineering recently. Academics [154] supported utilizing wind energy in small or medium size distributed arrangements. Kinds of renewable sources such as small wind turbines, photovoltaic, fuel cells, diesel engines, micro turbines, compose distributed energy resources (DER) and its derivative concept of Micro Grid (MG). MG is allowed to compete economically with traditional centralized electricity plant. It can either be operated in an isolated mode, or interconnected to the distribution network. H. Jiayi conducted a literature survey in [155] to introduce how the MG operated in both environments. The literature points out that only a few works have considered problems existing in situations where MG and ETS coexist. Furthermore, no research has investigated the impact of both ETS and RESS on the RES's operation. Besides CM and mandatory RM, voluntary RM has also been growing rapidly in recent years. It has created a platform for the entities or individuals to voluntarily reduce their carbon footprints. On one hand, consumers in the voluntary RM can purchase credit such as REC in the markets, which are generated from an eligible renewable resource. On the other hand, they can directly obtain credits from small MG project. Whether the RM is mandatory or voluntary, the development of ETS is likely to benefit RM, both in depth and breadth. Such as in U.S., the value of a REC, often speculative because it is determined by public policy rules, can include emissions reductions, regulatory compliance and evidence showing the generation or purchase of renewable energy. So far no literature has studied the joint effects of ETS and RESS on GENCOs operation in electricity market. To consider wind power uncertainty under multimarket environment, a novel dynamic decision making model is proposed for GENCO in chapter 7. This study includes the probability of stochastic wind power based on non-linear wind power curve and Weibull distribution. Different scenarios of climate polices will be compared to demonstrate their economic and environmental influences on a GENCO.

2.5. Summary

In this chapter, existing studies relevant to the research objectives of the thesis have been reviewed. From the literature review, the following conclusions can be drawn:

A. Since the pricing mechanism is the most significant component in electricity market, novel models related to pricing scheme should be developed for both active power and reactive power.

B. Previous studies of day-ahead electricity price forecasting are classified and compared in section 2.2.2. Current available literatures on reactive power pricing are reviewed in section 2.2.3. More effective methodologies are needed to deal with price forecasting and reactive power pricing in electricity market planning and management.

C. Fundamental issues of emission trading scheme, which play a significant role to link the four interactive markets including electricity market, carbon market, fuel market and renewable market, are discussed in section 2.3. Background of ETS and the international situation of carbon markets are presented, followed by the research problems of implementing ETS and the comparisons of ETS with other climate policies.

D. A comprehensive interaction analysis among electricity market, carbon market, fuel market and renewable market is presented in section 2.4. The analysis is provided through investigating the impacts of emission trading scheme on each markets. Several unsolved problems are addressed in this section and shed some lights on chapters 5-8.

In summary, previous studies on electricity market planning and management, especially for pricing scheme, leave many rooms for further research exploration. Therefore, pricing schemes for both active power and reactive power are investigated in chapter 3 and chapter 4, respectively. The implementation of ETS in power industry has brought lots of research problems in electricity planning and management considering environmental and economical effects. Recent research progresses in ETS have been reviewed comprehensively and the interactions among electricity market, carbon market, fuel market and renewable market have been analysed in section 2.4. With consideration of environmental and economical influences under multi-market environments, several unsolved problems are addressed. Based on the literature review and interaction analysis, chapters 5-7 will investigate the following research topics which will enrich the study of environmental and economical analysis in electricity market planning and management significantly:

- Investigate the impacts of emission trading schemes on a GENCO's decision under multimarket environment
- Analyses the impacts of emission trading and renewable energy support schemes on electricity market operation
- Develop a novel decision making model for GENCO's operations considering emission trading and renewable energy support schemes.

CHAPTER 3. A NOVEL FRAMEWORK FOR ELECTRICITY MARKET PRICE FORECASTING

3.1. Introduction

As discussed in section 2.2.2, a number of techniques have been proposed for electricity price forecasting. However, available methods have their own demerits so that they cannot effectively deal with price forecasting in the electricity market. As chapters 5, 6 and 7 dedicate to propose planning and operation models for GENCOs under multi-market environments, a robust and accurate prediction model for day-ahead electricity price is of importance under these circumstances.

The difficulties of the electricity price forecasting in electricity markets with several interconnected regions is firstly presented in section 3.2 of this chapter. It is followed by the introduction of several evaluation criteria. Rare literature has studied both inter-temporal dynamics and inter-regional interactions of uniform day-ahead price among different interconnected regions. Panel cointegration (PC) model is creatively employed to forecast the day-ahead electricity market prices in section 3.3. It shows good performance but cannot handle the nonlinear patterns of the electricity prices series. Particle filter (PF) has achieved significant success in tracking applications involving non-Gaussian signals and nonlinear systems. To make use of the advantages of both techniques, section 3.4 creatively integrates the two technologies and proposes a novel estimation framework based on panel cointegration and particle filter (PCPF). The Pennsylvania—New Jersey—Maryland (PJM) market is chosen for the case studies in section 3.5,using the historical data of the PJM which are published at its website and can be found in [156].

3.2. Problem Formulation

A pool-based electricity market (EM) with *N* interconnected regions is studied in this section. In this kind of market (e.g. PJM), the operator coordinates the movement of electricity through the interconnected power grid. The uniform price in the day-ahead market is affected significantly by the regional loads because electricity price is calculated based on the consideration of the entire gird [24]. On the other hand, the variability of the uniform price can influence the energy-usage patterns and introduce new trends. Fig. 3-1 shows a snapshot of the seven regional loads of PJM from Jan 1 to Jan 7, 2008.

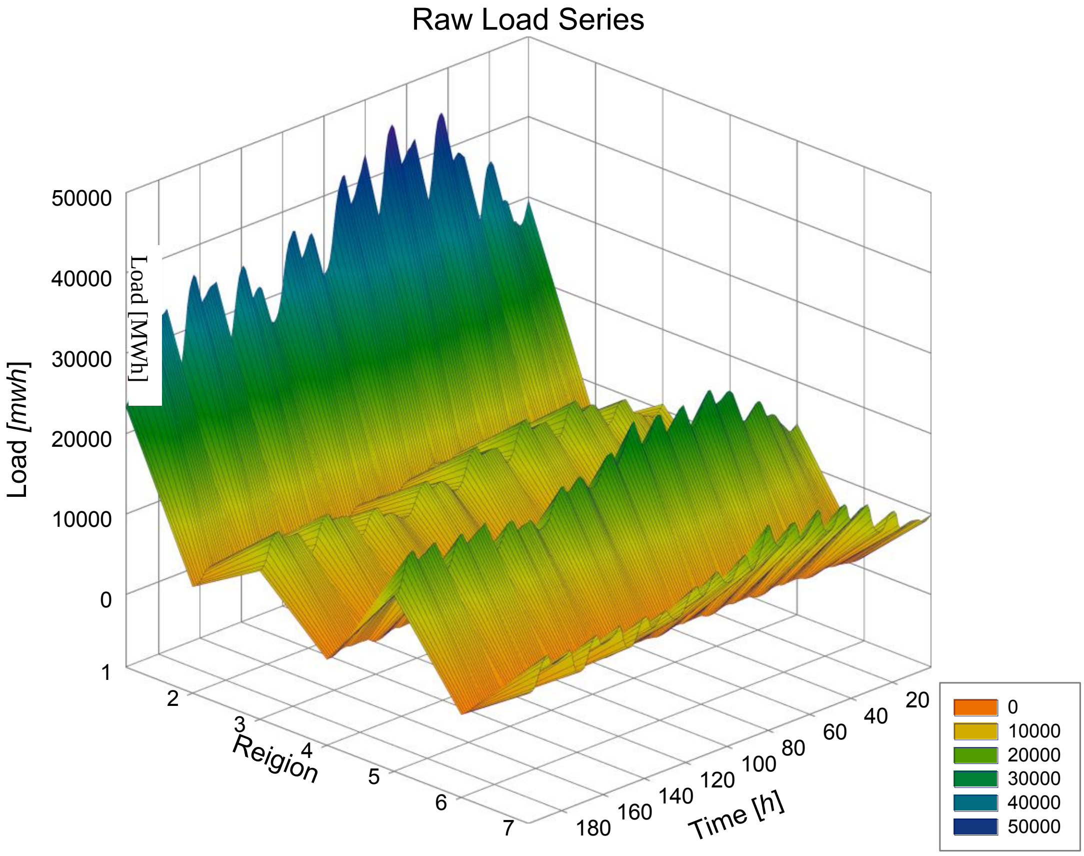

Fig. 3-1 Loads of the 7 regions from Jan 1, 2008 to Jan 7, 2008

It can be seen that significant loading differences, which change from time to time, exist among regions. Besides, significant individual intra-day variations can be observed. In other words, both the inter-temporal dynamics and the inter-regional interactions exist in the panel of data. The dynamics of electricity price and loads are always non-stationary due to the discrete changes in participants' strategies from different regions so that individual time series analysis cannot simultaneously reflect electricity consumption conditions in different regions. In view of the disadvantages of time series data, the PC model presented in section 3.3 is used to identify both the impacts of inter-temporal dynamics and inter-regional load differences on the uniform day-ahead price. This is the first time a PC model has been applied in the electricity price forecasting.

In addition, nonlinear patterns exist in the relationship among the uniform day-ahead price and the loads of different regions. In this case, using time series models such as regression based models and stochastic time series models cannot capture the complex nonlinear behavior. On the other hand, using intelligent method such as NN will yield mixed results and the efficiency will vary from case to case. Considering these two aspects, the PCPF model is proposed in section 3.4 to tackle these difficulties by using a two-stage forecasting framework.

To assess and compare the performance of the models, weekly mean absolute percentage error (*WMAPE)*, WMAPE for period *j* (*WMAPEj*), daily mean absolute percentage error (*DMAPE*), weekly mean absolute error (*WMAE*) and weekly root mean square error (*WRMSE*) indices are adopted in this thesis.

$$WMAPE = \frac{1}{168}\sum_{t=1}^{7}\sum_{j=1}^{24}\frac{|X_{j,t}^{A} - X_{j,t}^{F}|}{X_{j,t}^{A}} \tag{3-1}$$

$$WMAPE_{j} = \frac{1}{7}\sum_{t=1}^{7}\frac{|X_{j,t}^{A} - X_{j,t}^{F}|}{X_{j,t}^{A}} \tag{3-2}$$

$$DMAPE = \frac{1}{24}\sum_{j=1}^{24}\frac{|X_{j,t}^{A} - X_{j,t}^{F}|}{X_{j,t}^{A}} \tag{3-3}$$

$$WMAE = \frac{1}{168}\sum_{t=1}^{7}\sum_{j=1}^{24}\left|X_{j,t}^{A} - X_{j,t}^{F}\right| \tag{3-4}$$

$$WRMSE = \sqrt{\frac{1}{168}\sum_{t=1}^{7}\sum_{j=1}^{24}(X_{j,t}^{A} - X_{j,t}^{F})^2} \tag{3-5}$$

where $X_{j,t}^{A}$ is the actual value and $X_{j,t}^{F}$ is the forecasted value of the predicted variable.

3.3. Proposed Panel Cointegration model

Panel cointegration model have been proved as a feasible forecasting tool in statistics and econometrics [157, 158]. It builds upon panel data which is a set of sample values which combines cross-sectional and time-series data sets. Either time series or cross-sectional data is a special case of panel data in one-dimension only. The panel cointegration model is applied to forecast electricity prices in [24] for the first time.

Mathematically, the panel data has N cross-sections (i.e. number of regions in EM) and T number of days in sample. The panel data is constructed as：

$$\begin{aligned}
&P_{j,t} = \beta_{0,j} + \sum_{l=1}^{m}\alpha_{0,j,l}P_{j,t-l} + \sum_{i=1}^{N}\beta_{i,j}L_{i,j,t} + \gamma_{j,t};\\
&L_{i,j,t} = e_{i,j} + \sum_{l=1}^{n}\alpha_{i,j,l}L_{i,j,t-l} + u_{i,j} + \delta_{i,j,t};\\
&(i = 1,2,...,N;\ j = 1,2,...,24; t = 1,2,...,T;\\
&\gamma_{j,t} \sim (0,\sigma_{\gamma}^{2});\ u_{i,j} \sim (0,\sigma_{u}^{2}); \delta_{i,j,t} \sim (0,\sigma_{\delta}^{2}))
\end{aligned} \tag{3-6}$$

where $\beta_{0,j}, \beta_{i,j}, e_{i,j}$ are coefficients for cross-section and $\alpha_{0,j,l}, \alpha_{i,j,l}$ are coefficients for time-series. l is the time lagged value in order to capture the distinct profile of each inter-day period. m and n are the number of time lagged items $P_{j,t-l}$ and $L_{i,j,t-l}$, respectively. The advantage of having panel data as compared to a single cross-section or series of cross-sections with non-overlapping cross-section units is that it allows us to test and relax the assumptions that are implicit in cross-sectional analysis [159]. To estimate the long-run equilibrium relationship and the short-run adjustment relationship among variables, three procedures need to be carried out: panel stationarity test, panel cointegration test and PC estimation.

The establishment of a PC model among variables requires to test whether the panel data is (i) stationary (integrated of order zero) or non-stationary (integrated of order one); and (ii) cointegrated. A stationary process is a stochastic process whose joint probability distribution does not change when shifted in time or space. Consequently, parameters such as the mean and variance, if they exist, also do not change over time or space. In general, electricity prices and loads are non-stationary variables that cannot be directly estimated [42]. Hence, cointegration is an alternative to describe their relationships in econometric analysis which indicates long term equilibrium among variables. Therefore, the cointegration test and PC estimation will be carried out if the panel data is non-stationary; otherwise the coefficients of the panel model can be directly estimated according to (3-6).

3.3.1. Panel stationarity test

Unit root test is a conventional econometric method to test the stationarity of time series by examining the existence of unit roots. Recent literature [160] finds that panel-based unit root tests are much more powerful than the basic tests such as Augmented Dickey–Fuller test [161] which are based on individual time series. The panel unit root test methods including Levin, Lin, and Chu (LLC) [162] and PP–Fisher Chi-square [163] are suitable candidates for examining the common unit root process and individual unit root process, respectively.

3.3.2. panel cointegration test

PC technique involves not only long-run relationship among non-stationary variables, but also short term fluctuation of stationary variables, which can help to achieve high forecasting precision.

In this chapter, Johansen Fisher Panel Cointegration (JFPC) test [164] is used to examine the existence of determined cointegration relationship among the variables. The JFPC test allows the existences of both stationary and non-stationary variables in the panel. This method permits more than one cointegration relationship and hence it is generally applicable in testing the panel data. Once cointegration relationships are ascertained within the constructed panel data, the coefficients of PC model can be estimated according to (3-7) described in the next sub-section. Otherwise, the variables in the panel will be processed by another operators [163, 165] in which $P_{j,t}, L_{i,j,t}$ in (3-6) will be replaced by $\Delta P_{j,t}, \Delta L_{i,j,t}$ and then the reconstructed panel data will be re-tested.

3.3.3. Panel cointegration estimation

Based on the validated cointegration within a panel of N cross-sections, PC model can be established. PC can lead to a better understanding of the nature among different component series and also improve long term forecasting with an unconstrained model. A PC model is expressed as follows:

$$
\begin{aligned}
\Delta P_{j,t} &= P_{j,t} - P_{j,t-1} \\
&= C_j + \Pi ECM_{j,t-1} + \sum_{l=1}^{m} \Phi_{j,l} \Delta P_{j,t-l} + \sum_{i=1}^{N} \sum_{l=1}^{n} \Psi_{i,j,l} \Delta L_{i,j,t-l} + \tau_{j,t} \\
\text{where} \quad & ECM_{j,t-1} = P_{j,t-1} - \sum_{i=1}^{N} \xi_{i,j,t-1} L_{i,j,t-1} + \phi_{j,t-1}, \\
& \Pi = \begin{pmatrix} \Pi_1 & & & \\ & \Pi_2 & & \\ & & \ddots & \\ & & & \Pi_J \end{pmatrix}_{Jr \times Jr}
\end{aligned} \tag{3-7}
$$

where C_j is the common coefficient for each trading period *j*. *J* is the number of market clearing periods within a day. The dimension of each sub-matrix Π_j within the diagonal matrix Π is $r \times r$. The dimension of the matrices $ECM_{j,t-1}$ and $\Phi_{j,l}$ is $j \times \mathrm{r}$. The dimension of the diagonal matrix Π_j is $j \times j$. The sub-matrices relate $\Delta P_{j,t}$ to the error correction item $ECM_{j,t-1}$. $\xi_{i,j,t-1}$ is the coefficient for error correction. *r* denotes the number of regressors (variables in the regression) in the explanation item $ECM_{j,t-1}$ which reflects long term cointegration relationship for the panel, i.e. it describes a kind of long term adjustment for deviating the equilibrium relationship. Besides long term adjustment, the PC model also involves short term fluctuation items $\Delta P_{j,t-l}$, $\Delta L_{i,j,t-l}$. The coefficient matrix $\Phi_{j,l}$ captures the dynamics within time domain while $\Psi_{i,j,l}$ correlates the variability of the price with both the inter-temporal dynamics and the inter-regional interactions among regional loads. Adding the error correction features to the panel data, the disadvantage of traditional forecasting models which lose the long term information collected from variables can be overcome.

Maximum likelihood estimator is employed to predict the coefficients. A variable elimination procedure is then processed to reduce the redundancy and complexity of the model. The coefficients with relatively higher statistical significance (based on the corresponding standard error and T-statistics) are used to formulate the PC model. As the cointegration relationship is assumed dynamic, the responses of price to various market fundamentals may change continuously. The performance of PC models will be compared with other models in section 3.5.

3.4. Proposed Panel Cointegration and Particle Filter Model

The proposed novel panel cointegration and particle filter (PCPF) model has two features that differentiate it from other existing techniques. First, it makes prediction by using historical loading data of different regions in the pool and constructs the regional loading data together with the uniform day-ahead price as a panel [165].

Using panel data, both the impacts of inter-temporal dynamics and inter-regional loading differences on the uniform day-ahead price can be taken into account. Secondly, PF is applied as a post-processor to effectively handle the nonlinearity and the volatility of electricity price. Other than loading data, there are many other factors which can affect the price forecasting performance. The two-stage model incorporates historical loading data, the most important factor, in panel cointegration. The other factors are treated as uncertainties which are simulated by particle filter. Both PC and PF models have achieved successes in their own linear or nonlinear domains. However, none of them is a universal model that is suitable under all circumstances. For example, on one hand, the approximation of PC models for complex nonlinear problems may not be adequate. On the other hand, using PF to model linear problems has yielded mixed results [166]. Since it is difficult to fully realize the characteristics of the data in a real problem, it is reasonable to consider day-ahead electricity series to be composed of both linear autocorrelation structure and nonlinear patterns. Combining different models, different aspects of the underlying patterns may be captured. PCPF which has both linear and nonlinear modeling capabilities can be a good strategy for practical use.

As it is unlikely to include all market fundamentals into a price forecasting model, the proposed model takes the most important factors into account in the PC model which has been introduced in section 3.3 and then treats the others as uncertainties which will be handled by PF. As the change in regional loads is the key factor that affect the uniform electricity price, this model uses historical regional loads and price as input variables to predict the price although other factors can be incorporated easily. This model is based on a two-stage architecture shown in Fig.3-2.

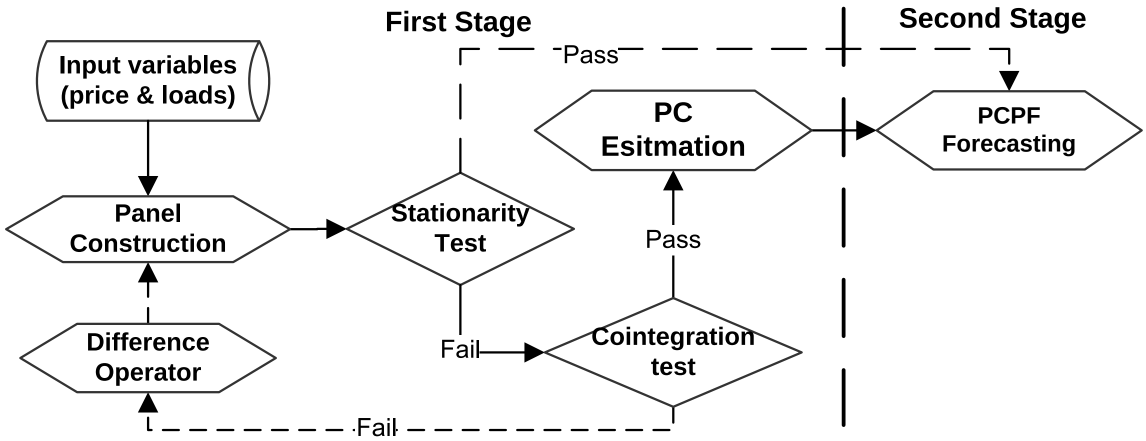

Fig. 3-2 Two-stage PCPF model for electricity forecasting

The coefficients with relatively higher statistical significance (based on the corresponding standard error and T-statistics) in the PC model in the first stage are inputted to the second stage. The coefficients estimated in the PC model can be regarded as a time-varying process so that the PF can adaptively give forecasting similar to agents' learning according to subtle rule modifications described in the second stage. The performance comparison among the PC, PCPF and some selected intelligent learning models introduced in section 2.2.2 will be investigated in the case study.

3.4.1. Architecture of the PCPF model

Little attention has been paid to develop methods that can handle both linear and nonlinear problems simultaneously. Therefore, a novel PCPF model based on hybrid architecture is proposed in this chapter to predict day-ahead electricity price. The PCPF can be mathematically presented as the following state space representation:

$$\begin{aligned} P_{j,t} &= X'_{j,t}\lambda_{j,t} + \varepsilon_{j,t} && \text{Measurement Function} \\ \lambda_{j,t} &= f_{j,t}(\lambda_{j,t-1}, \nu_{j,t}) && \text{Transfer Function} \end{aligned} \tag{3-8}$$

where $\varepsilon_{j,t} \sim i.i.d.N(0, \sigma^2_{\varepsilon_{j,t}}),\ \nu_{j,t} = (\nu_{j1t}, \nu_{j2t}, \nu_{jkt} \ldots \nu_{jKt})'$,
$\nu_{j,t} \sim N_k(0, \Sigma_j),\ E(\varepsilon_{j,t}\nu_{j,t}) = 0$, and $\Sigma_j = diag\{\sigma^2_{\nu_{j,k}}\}$

In the measurement equation, matrix $P_{j,t}$ represents the uniform day-ahead prices in period j on day t. There are K input variables $\in \{1, \Delta P_{j,t-l}, \Delta L_{i,j,t-l}, P_{j,t-l}, L_{i,j,t-l}\}$ in each element of the matrix $X_{j,t}$, K is the number of regressors after the application of a variable elimination procedure carried out in (3-7). These regressors (variables) will be used for forecasting in the second stage. Notice that both $\varepsilon_{j,t}$ and $\nu_{j,t}$ follow Gaussian distribution $i.i.d.N(0, \sigma^2_{\varepsilon_{j,t}})$ and $N_k(0, \Sigma_j)$, respectively and independently. In the transfer equation, $f_{j,t}(\cdot)$ is a nonlinear function where $\lambda_{j,t}$ will be obtained recursively via PF processing. The coefficients $\lambda_{j,t}$ are not unknown constants but latent stochastic that follow random walks. PF achieves this by obtaining an optimal approximation of posterior distribution for $\lambda_{j,t}$.

In the first stage, we let PC to model both the inter-temporal dynamics and the inter-regional interactions of uniform day-ahead price among different regions through the cointegration analysis based on panel construction; then the residuals from the PC model will contain only the nonlinear pattern. To handle the nonlinear pattern and also uncertainties, the coefficients matrix $\lambda_{j,t}$ in the transfer equation is considered as a set of time-varying particles following random walks so that it enables the coefficients to react to the arrival of new observations. The disturbance terms $\varepsilon_{j,t}$ follow the fitting distribution of estimation residues and the variance of the process noise can be estimated from the variances of the particles, regarding to the previous PC coefficients at time (*t*-1) as follows:

$$\sigma^2_{v_{j,k}} = \sigma^2_{v_{j,k}(t-1)}(\frac{1}{g} - 1) \tag{3-9}$$

where *g* is called as the “forgetting factor” and takes values between zero and one. Different from Kalman filter [167], the stochastic variables in $\lambda_{j,t}$ are considered nonlinear and estimated by PF for each period *j* simultaneously on day *t*.

3.4.2. Particle filter forecasting

Particle filter (PF) is particularly successful in dealing with nonlinear and non-Gaussian problems [167, 168]. Unlike the extended Kalman filter, which only use the mean and variance to describe the distribution of a state, PF utilizes sequential Monte Carlo method to approximate the optimal filtering, using particles to represent the probability density function (PDF) of a state. The number of particles is equal to the number of regressors described in the last sub-section. The main task in the second stage is to estimate $\lambda_{j,t}$ based on the arrival of the new observations $P_{j,t}$ so that the day-ahead electricity price $P_{j,t+1}$ can be obtained using (3-8) for each period *j* on day *t*.

A feature of PF is to approximate the posterior distribution of $\lambda_{j,t}$ by a collection of *K* weighted particles:

$$\lambda = \{\lambda^k_{j,t}, w^k_{j,t}\}^K_{k=1} \tag{3-10}$$

where $w^k_{j,t}$ is the weight of the particle $\lambda^k_{j,t}$, and the posterior probability of the random event $\lambda_{j,t}$ is approximated as follows:

$$p(\lambda_{j,t} \mid P_{j,0:t}) \approx \sum_{k=1}^{K} w^k_{j,t-1}\delta(\lambda_{j,t} - \lambda^k_{j,t-1}) \tag{3-11}$$

We therefore have a discrete weighted approximation to the true posterior $p(\lambda_{j,t} \mid P_{j,0:t})$. It is the conditional probability that is assigned to $\lambda_{j,t}$ after all available measurements up to day t (abbreviated as $P_{j,0:t}$) have been observed. Dirac-delta function $\delta(\cdot)$ means to perform the integral function. Since it is difficult to draw samples from $p(\lambda_{j,t} \mid P_{j,0:t})$, importance function $q(\cdot)$ is usually adopted to generate K particles as follows:

$$\lambda_{j,t}^k \sim q(\lambda_{j,t} \mid \lambda_{j,0:t-1}^k, P_{j,0:t}) = \sum_{k=1}^{K} w_{j,t-1}^k p(\lambda_{j,t} \mid \lambda_{j,t-1}^k) \tag{3-12}$$

where the weights in (3-11) are updated accordingly as:

$$w_{j,t}^k \propto w_{j,t-1}^k \frac{p(P_{j,t} \mid \lambda_{j,0:t}^k) p(\lambda_{j,t}^k \mid \lambda_{j,t-1}^k)}{q(\lambda_{j,t}^k \mid \lambda_{j,0:t-1}^k, P_{j,0:t})} \tag{3-13}$$

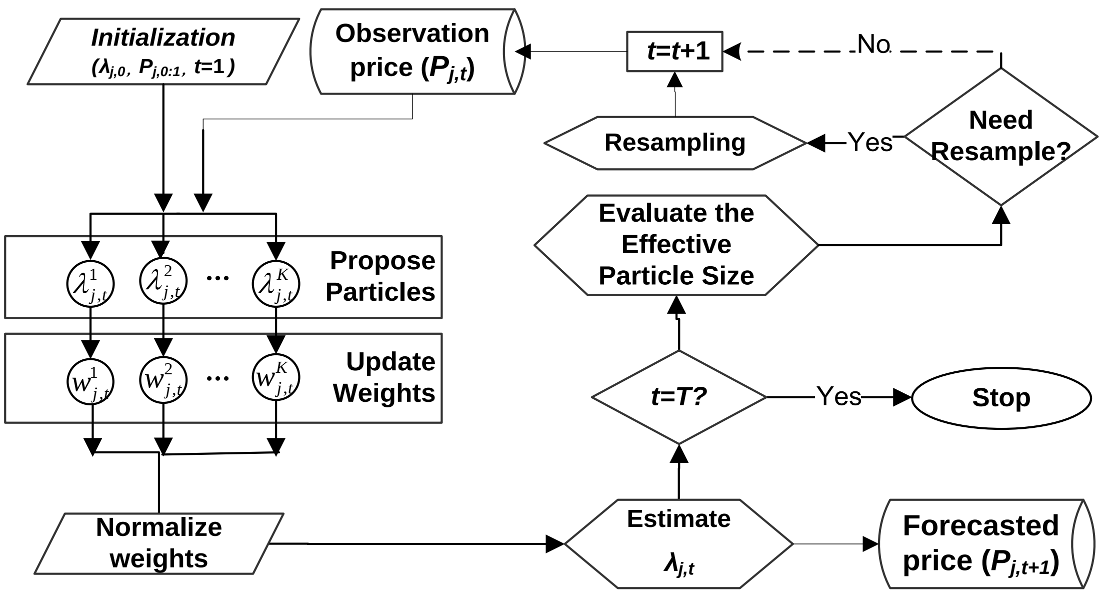

Fig. 3-3 Particle filter forecasting for period *j*

The importance function $q(\cdot)$, known as a proposal conditional distribution, is important in the performance of the PF. In general, the closer the importance function $q(\cdot)$ to the distribution of $p(\cdot)$, the better the approximation is.

In this study, $q(\lambda_{j,t} \left| \lambda_{j,0:t-1}^{k}, P_{j,0:t}\right.)$ has been chosen as the optimal importance function. This is because $q(\cdot)$ can minimize the variance of the true weights and hence the degeneracy problem is diminished in one way only. The details of choosing the optimal importance function can be found in [169] and is outside the scope of this thesis. For each period *j*, the forecasting architecture of the PF is illustrated in Fig. 3-3.

The PF algorithm is illustrated for each period *j* in the following pseudo-codes and its main task is to estimate the state $\lambda_{j,t}$ recursively from the observations $P_{j,t}$.

---

(1) Initialization:

- Set $t=1$, $w_{j,t}^{k}=1/K$

(2) Prediction:

For k =1: K

- Generate particles $\lambda_{j,t}^{k} \sim q(\lambda_{j,t} \left| \lambda_{j,0:t-1}^{k}, P_{j,0:t}\right.)$ according to (3-12)
- Assign each particle an updated weight $w_{j,t}^{k}$ according to (3-13)
- Normalize the weights according to $\{w_{j,t}^{k}\}_{k=1}^{K} = w_{j,t}^{k} \Big/ \sum_{k}^{K} w_{j,t}^{k}$
- The PDF of $\lambda_{j,t}^{k}$ is approximated so that the estimated electricity price $P_{j,t+1}$ can be computed using (3-8)
- End **For**

(3) Particle Size Evaluation :

- Evaluate the effective size of particles by counting the percentage of particles with weights smaller than a certain value. If the percentage is below a predefined threshold, *Resampling* takes place; otherwise proceed to *Iteration*

(4) Resampling:

- Sample $\{u_k\}_{k=1}^{K} \sim U[0,\ 1]$ and K particles $\tilde{\lambda}_{j,t}^{k} \sim p(\lambda_{j,t} | P_{j,0:t})$
- Replace $\{\lambda_{j,t}^{k}\}_{k=1}^{K}$ with $\{\tilde{\lambda}_{j,t}^{k}\}_{k=1}^{K}$ if $u_k < \min\{1, p(P_{j,t} | \lambda_{j,0:t}^{k}) / p(P_{j,t} | \lambda_{j,t}^{k})\}$
- Assign particles an equal weight

(5) Iteration:

- **For** t =1: T-1
- Set $t = t + 1$, Obtain the day-ahead electricity price $P_{j,t}$ observation and update $P_{j,0:t}$
- Go to **Prediction**
- End **For**

A major problem with particles filtering is that the discrete random measure degenerates quickly. Besides adopting the optimal importance function, ***Resampling*** is also used [166] since it can avoid the increasing of the variance of the particle weights. In this step, K particles are drawn from the current particle set with probabilities proportional to their weights. Particles with higher importance weights are replicated, while the others are discarded.

3.5. Experiments on the two proposed models

In this section, criteria defined in section 3.2 are employed to evaluate the performance of the proposed PC and PCPF models. The PJM day-ahead electricity market data are chosen to test the proposed framework. It is a market with 7 regions in which hourly prices are cleared. The inputs include time lagged values of price and loads which are available on the PJM's website [156]. The data of PJM's in the period Jan 1, 2007 –Dec 31, 2007 are used in the PC model for the coefficients estimation. To compare the two models coherently and fairly, the estimated coefficients of PC model are inputted into the second stage of the PCPF model. The real market data in the year 2008 is used to test the effectiveness of the proposed models.

3.5.1. Experiment on the panel cointegration model

Model (3-6) is used to describe the linear pattern of day-ahead electricity prices based on panel construction. To examine the stationarity of all the series of the panel variables and clarify the stochastic nature of the price dynamics, unit-root tests employing LLC and PP–Fisher Chi-square methods [170] method, as shown in Table 3-1, are used to test the presence of unit root in the panel data in different time periods.

Table 3-1 Panel unit root test results

Method	**Levin, Lin & Chu***		**PP–Fisher Chi-square****	
Null Hypothesis	**Common Panel Unit Root Probability**		**Individual Panel Unit Root Probability**	
Period (*j*)	$L_{i,j,t}$	$P_{j,t}$	$L_{i,j,t}$	$P_{j,t}$
j=1	0.201	0.000	0.897	0.312
j=2	0.219	0.000	0.906	0.280
j=3	0.216	0.000	0.904	0.065
j=4	0.209	0.0050	0.897	0.091
j=5	0.195	0.000	0.888	0.033
j=6	0.182	0.003	0.881	0.000
j=7	0.154	0.011	0.861	0.000
j=8	0.142	0.016	0.854	0.000
j=9	0.154	0.011	0.866	0.001
j=10	0.185	0.026	0.889	0.009
j=11	0.191	0.028	0.892	0.006
j=12	0.151	0.040	0.852	0.034
j=13	0.148	0.033	0.849	0.082
j=14	0.139	0.025	0.841	0.006
j=15	0.156	0.008	0.864	0.014
j=16	0.154	0.006	0.861	0.013
j=17	0.144	0.007	0.851	0.043
j=18	0.163	0.009	0.869	0.058
j=19	0.169	0.007	0.874	0.093
j=20	0.177	0.000	0.880	0.103
j=21	0.188	0.000	0.888	0.190
j=22	0.198	0.001	0.895	0.336
j=23	0.212	0.000	0.902	0.396
j=24	0.257	0.000	0.923	0.468
Note:	1.**, * denote significance at 5%, 10% level 2.All tests assume asymptotic normality			

It can be seen that the results in different periods listed in Table 3-1 tend to be consistent. The LLC test assumes that there is a common unit root process in the panel. This assumption can be rejected if the probability is less than 0.1. Standing on 10% level of significance, null hypothesis of a common unit root process (i.e. the homogeneous panel series are non-stationary) can be rejected in the price series but not in the load series. Similarly, standing on 5% level of significance, null hypothesis of individual unit root process (i.e. the heterogeneous panel series are non-stationary) cannot be rejected in all the load series and most of the price series. Hence, it can be concluded that the panel model cannot be directly used for forecasting since not all the included series are stationary.

Based on the empirical results that each panel contains at least one panel unit root, JFPC is conducted to examine the cointegration relationships among variables. JFPC is a robust trace based cointegration test with the null hypothesis for the number of cointegration vectors. Standing on 10% level of significance, Table 3-2 shows that all the probabilities for the null hypothesis of none cointegration are nearly zero. This suggests that cointegration relationship exists in the constructed panel in all the periods. Hence, the coefficients of the PC model (3-7) can now be estimated.

Table 3-2 Panel cointegration test results

Null Hypothesis: None Cointegration ***Note: the significance of the test is at 10% level***						
Period (*j*)	**1**	**2**	**3**	**4**	**5**	**6**
Probability	0.003	0.000	0.000	0.001	0.001	0.014
Period (*j*)	**7**	**8**	**9**	**10**	**11**	**12**
Probability	0.039	0.018	0.000	0.000	0.000	0.000
Period (*j*)	**13**	**14**	**15**	**16**	**17**	**18**
Probability	0.005	0.043	0.000	0.001	0.000	0.000
Period (*j*)	**19**	**20**	**21**	**22**	**23**	**24**
Probability	0.000	0.000	0.002	0.000	0.000	0.000

The derived coefficients Π, $\Phi_{j,l}$, $\Psi_{i,j,l}$ in the PC model correspond to $\lambda_{j,t}$ in the PCPF model (3-8). The coefficients are predicted by maximum likelihood estimator. Owing to space constraint, only the estimated coefficients with relatively higher statistical significance derived from the PC model (3-7) in period 1 are listed in Table 3-3. The standard error and T-statistics indicate the contributions of each variable to the PC model, which are also the evaluation criteria for selecting coefficients inputted to the second stage. Based on the estimated coefficients, a continuous simulation of point forecasting in all periods from Jan 1, 2008 to Dec 31, 2008 are conducted in this experiment. The details of the forecasting results will be given in section 3.5.3

Table 3-3 Estimated coefficients of PC model

Variable $\lambda_{1,t}(k)$	**Coefficient**	**Standard Error**	**T- Statistics**
k=183	0.039	0.020	2.010
k=42	0.002	0.001	1.629
k=177	0.009	0.006	1.588
k=176	0.008	0.006	1.485
k= 162	0.014	0.010	1.395
k=182	0.024	0.018	1.373
k=161	0.014	0.010	1.361
k=170	0.010	0.008	1.316
k=36	0.002	0.002	1.295
k=158	0.015	0.011	1.281
k=186	0.031	0.025	1.256
k=157	0.015	0.012	1.214
k=155	0.016	0.013	1.209
k=185	0.030	0.025	1.194
k=184	0.027	0.022	1.190

3.5.2. Experiment on the panel cointegration and particle filter model

As described in section 3.2.3, the coefficient matrices obtained in the first stage capture the dynamics of the price with both inter-temporal dynamics and inter-regional interactions among regional loads. However, due to the nonlinear composition of the electricity price and its variability, PF is adopted to capture the nonlinear patterns according to model (3-8). The efficiency of the proposed PCPF model is mainly dependent on the appropriate adjustments of its parameters. There are two main adjustable parameters: number of particles *K* and the time-varying coefficient matrix $\lambda_{j,t}$. To balance the efficiency and accuracy, the size of particles (*K*) which affects the computation time dominantly is better to be controlled between 100 and 200. In this experiment, *K* is equal to the number of coefficients$\lambda_{j,t}$ after the variable elimination process. Different from the other techniques, the proposed PCPF model is an adaptive forecasting tool which can automatically adjust the time-varying coefficient matrix $\lambda_{j,t}$. based on the observation data with minimum reliance on the heuristics.

Similar to the experiment described in section 3.5.1, the continuous simulation is conducted on the same time periods. It consumes 4 hours and 48 minutes when the size of particles is fixed at 200, which indicates that the average time for one day-ahead forecasting is less than one minute. All the computation times are measured on a Dell 2.66GHz personal computer with 2GB RAM. Therefore, the proposed PCPF is practical within a day-ahead decision-making framework.

3.5.3. Analysis of the experiment results

To illustrate the behaviors of the proposed modeling, results comprising of four weeks in January, May, September and December (months 1, 5, 9 and 12) corresponding to the four seasons in 2008 are presented in Figs 3-4 –Figs 3-8. In this manner representative results for the whole year can be provided. It should be noted that the accuracy for the weeks of spring and summer are around 93% while of autumn and winter are around 95%. Comparing with other relevant studies [168, 171, 172], these results are accurate for a study spanning one whole year.

To demonstrate the superiority of the proposed model, forecasting results of the four selected weeks using the proposed PCPF and other techniques including PC, NN[33], FNN[42] and RVM [172] are compared in Fig. 3-4- Fig.3-8. The spring week is from 17 Jan to 24 Jan; the summer week is from 3 May to 10 May; the autumn week is from 22 Sep to 29 Sep; the winter week is from 21 Dec to 28 Dec. Note that criteria for selecting the four representative weeks include unstable behaviors or drastic variations. Although these unsteady behaviors make forecasting difficult, the proposed PCPF model has good performance in daily forecasting with an average *DMAPE* below 5% in each studied week.

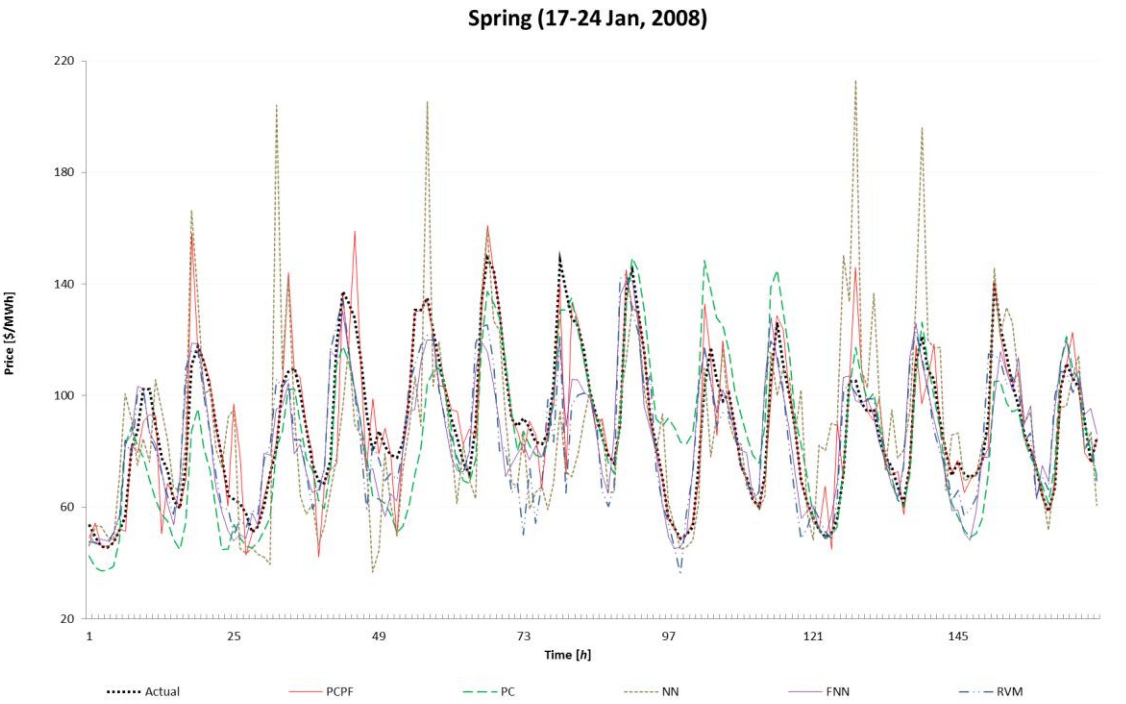

Fig. 3-4 Spring week forecasting

For the spring week, Fig.3-4 shows the comparison of the actual and forecasted prices. The prediction behavior of the proposed PCPF for the spring week is relatively better with a *WMAPE* of 7.3% while *WMAPE* of the PC technique is 15.6%. Hence, the postprocessor PF reduces the forecasting error by around 50%. Although the PC technique has some over-predictions of the mild spikes (20% over the usual peak), it has a good performance in estimating the transition tendency. The prediction behavior of NN in this representative spring week is less accurate than its counterparts since the price in this selected week varies considerably. With the adjustments provided by fuzzy logic, FNN (with a *WMAPE* of 14.0%) improves the forecasting performance of NN by around 32%. RVM shows a moderate forecasting performance with a *WMAPE* of 14.3%.

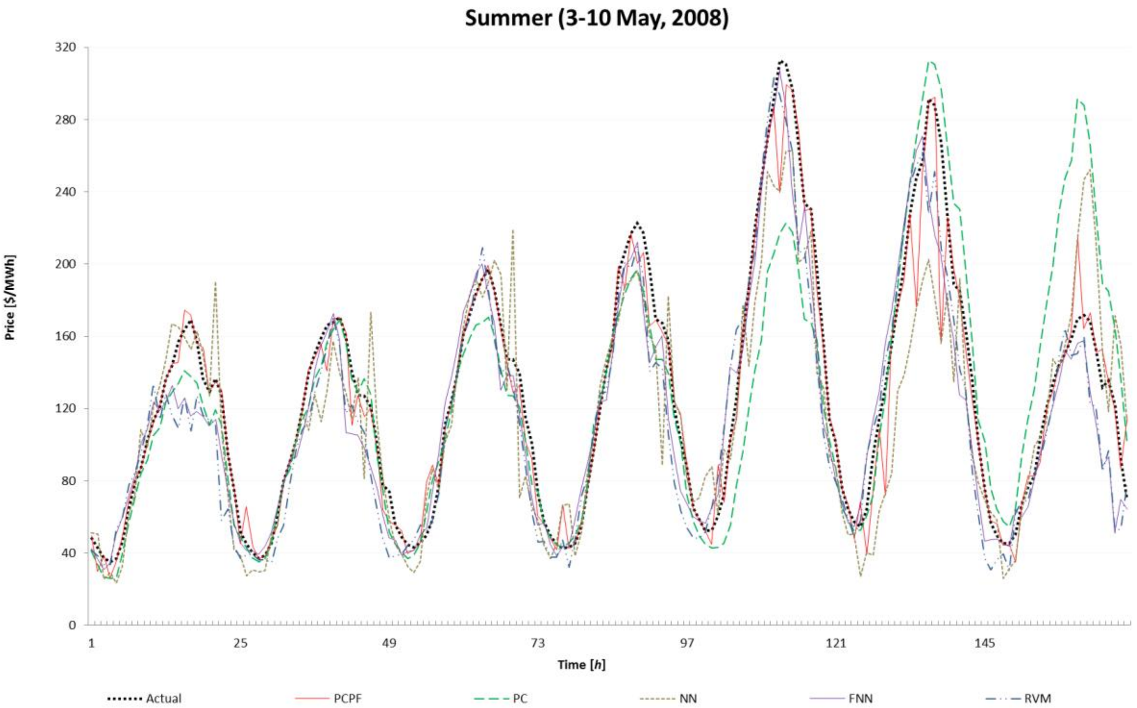

Fig. 3-5 Summer week forecasting

Refer to Fig.3-5, the reason of selecting this week is because it has the highest price in the whole year of 2008 (the peak was between hour 109 and hour 121). Owing to the seasonality, the number of crest is cut down by one half (i.e. two price peaks reduce to one within a day). The predictions of PC and NN are inaccurate with *WMAPE* of 18.0% and 20.3%, respectively. RVM, with a *WMAPE* of 17.2%, forecasts slightly better than PC and NN. Observe that the price pattern in this week is particularly unstable, probably owing to the strategic behavior of the dominant players in the market. FNN, with a *WMAPE* of 20.3%, reduces the error of NN by 26% while PCPF, with a *WMAPE* of 7.3%, reduces the error of PC by more than 60%.

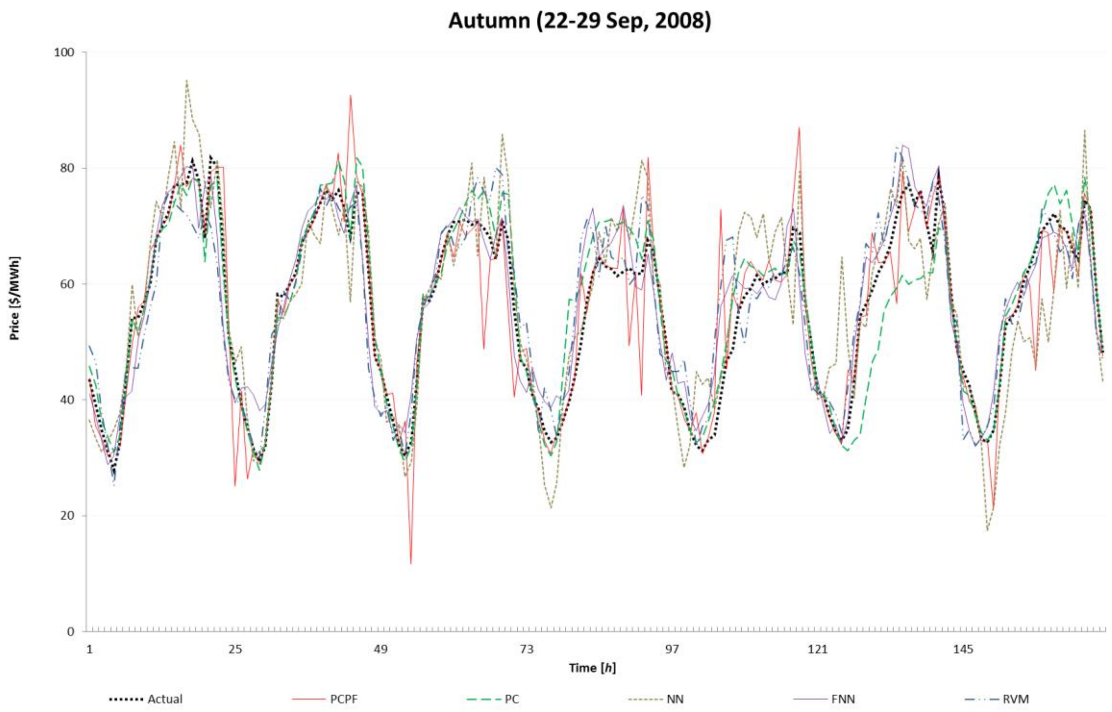

Fig. 3-6 Autumn week forecasting

As shown in Fig.3-6, the selected autumn week has relatively good forecasting behaviors. The peaks have no drastic changes as compared with that appeared in the previous seasons. Because of the less anomalous fluctuations and higher autocorrelation in the autumn series, all the three techniques show good forecasting performances. The values of *WMAPE* for PC, NN and RVM are 6.4%, 11.68% and 9.8%, respectively. PC performs better than that in the spring and summer weeks due to the better price pattern. Comparing with PC, NN and RVM, the forecasting by FNN and PCPF are more accurate most of the time. The *WMAPE* of FNN and PCPF are 6.3% and 9.0%, respectively. However, the PCPF would sometimes over-estimate the wild peaks.

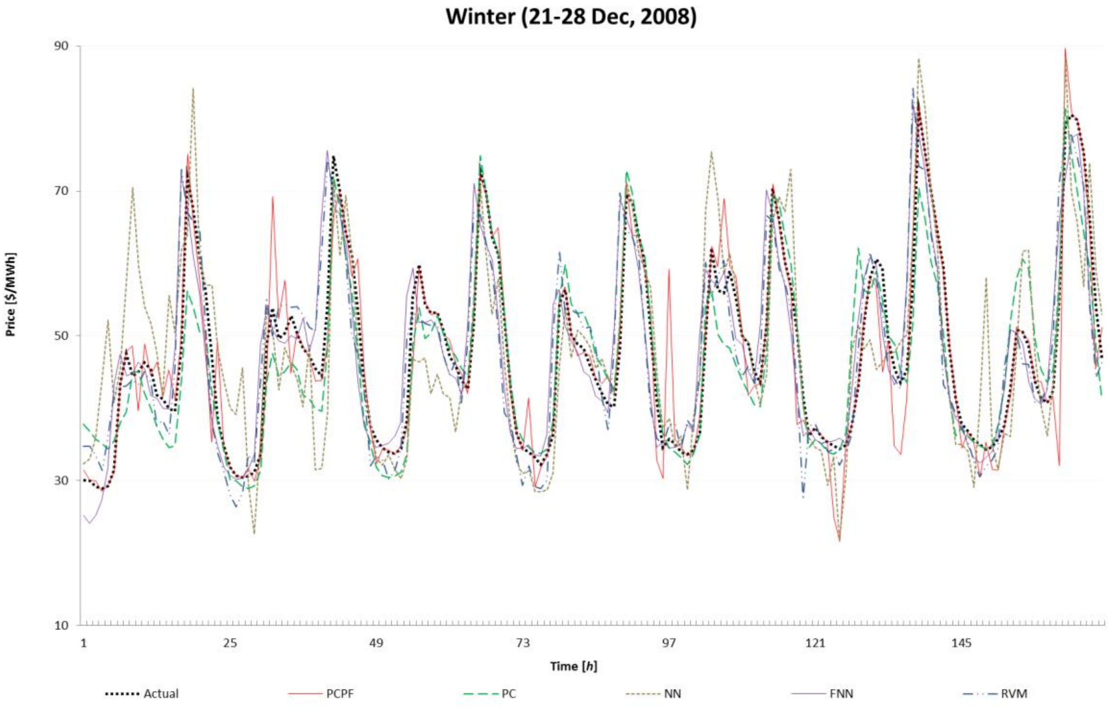

Fig. 3-7 Winter week forecasting

As for the winter week, the prediction is difficult resulting from the significant changes in prices between hours within a day. Because of the seasonality, there are only one low crest and one high crest instead of two similar crests within a day. This drastic change also leads to the difficulties in the forecasting. The values of *WMAPE* for the NN, FNN and RVM techniques are 13.3%, 10.2% and 10.9%, respectively. After a long evolution of particles, PCPF performs stably with *WMAPE* of 5.6% while *WMAPE* of PC is 8.3%.

Fig.3-8 shows $WMAPE_j$ of PCPF, PC, NN, FNN and RVM methods for the four test weeks. PC is the panel cointegration methodology introduced in section 3.3. NN is the Radial basis function neural network. FNN is the fuzzy neural network. RVM is the relevance vector machine method. The circle axis denotes the plotting hours while the vertical axis refers to the error percentage.

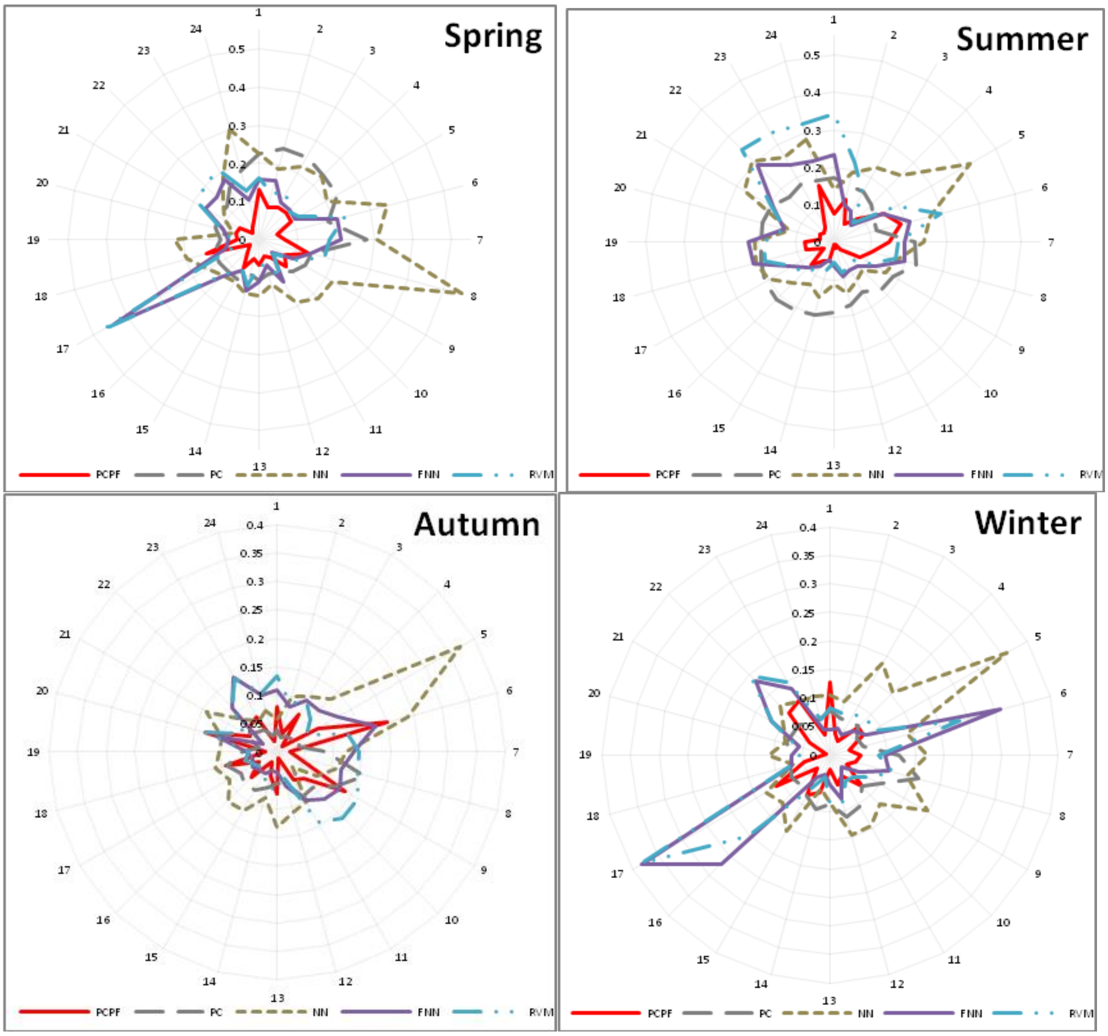

Fig. 3-8 $WMAPE_j$ for the four selected week

Among all the compared techniques, the performance of NN is sometimes far from satisfactory. $WMAPE_j$ are usually above 15% and deviate from the actual price at price peaks or minima. One of the major reasons for these problems is that the available data are insufficient at some peaks or minima which represent weak statistical samples for an algorithm based on historical-data learning. FNN improves NN's performance significantly though it has some large deviations in some hours. Similar to FNN, RVM forecasts stably except hour 17 in spring and winter. $WMAPE_j$ of PC is within 30% and usually around 20%. Comparing with PC, PCPF (with $WMAPE_j$ within 10%) has better accuracy and its performance is stable for most datasets. At some hours, PCPF even reduces the forecasted errors nearly to 1%. PCPF shows strong forecasting capability since its hybrid structure captures different aspects of the underlying patterns. This superiority is especially clear when comparing with the other techniques.

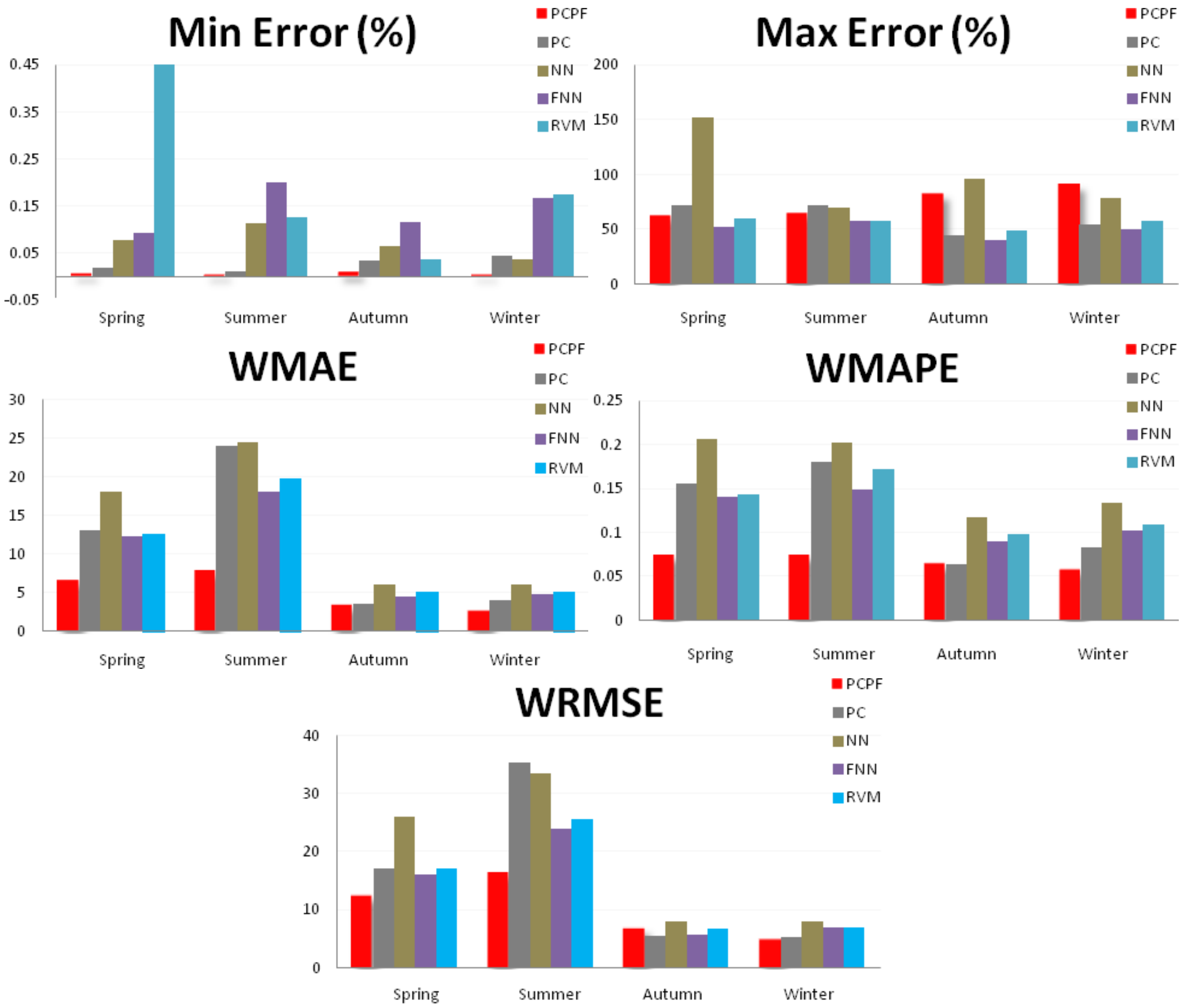

Fig. 3-9 Comparison of indices of the five techniques

The superiority of the PCPF technique is more evident when referring to Table 3-4. Notice that the performance of the PCPF technique is generally better than that of the other techniques. The values of WMAE and average WMAPE are smaller in all the scenarios. Furthermore, FNN and PCPF improve the forecast capability of NN and PC through their hybrid structure, respectively. When comparing th e improvements made by PCPF and FNN, PCPF shows a stronger error correcting capability than FNN. These results confirm the intuition that the hybrid model allows particles to evolve adaptively and to sequentially update a priori knowledge about some predetermined state variables given by PC

Table 3-4 Summary of forecasting results

Season	*Criteria*	*PCPF*	*PC*	*NN*	*FNN*	*RVM*
Spring	WRMSE	12.225	17.115	25.982	16.130	16.978
	WMAE	6.523	13.105	18.145	12.308	12.675
	WMAPE	0.073	0.156	0.206	0.140	0.143
	Max Error (%)	61.866	71.361	152.220	52.371	59.197
	Min Error (%)	0.004	0.018	0.077	0.092	0.457
Summer	WRMSE	16.145	35.305	33.425	23.924	25.478
	WMAE	7.666	23.944	24.505	18.100	19.735
	WMAPE	0.073	0.180	0.203	0.149	0.172
	Max Error (%)	64.264	72.015	69.035	57.840	58.018
	Min Error (%)	0.003	0.010	0.112	0.199	0.125
Autumn	WRMSE	6.529	5.353	7.900	5.686	6.705
	WMAE	3.301	3.623	6.083	4.562	5.139
	WMAPE	0.063	0.064	0.117	0.090	0.097
	Max Error (%)	81.368	44.263	95.640	39.719	48.741
	Min Error (%)	0.008	0.032	0.064	0.114	0.035
Winter	WRMSE	4.793	5.143	7.858	6.919	6.853
	WMAE	2.604	3.982	6.039	4.830	5.109
	WMAPE	0.056	0.083	0.133	0.102	0.109
	Max Error (%)	89.712	54.214	78.304	49.614	57.522
	Min Error (%)	0.002	0.044	0.036	0.165	0.175

3.6. Summary

In chapter 3, a panel cointegration (PC) based approach is presented in section 3.3 for predicting the electricity market prices. PC, a newly applied statistical method, is introduced to expand the dimension of electricity price dataset from time series to panel data so that the dynamics of interconnected regions can be analyzed simultaneously and considered as a whole. It provides reasonable accuracies of electricity prices forecasting as shown in section 3.5. Nowadays day-ahead electricity market is closely associated with different commodity markets. Under this complex circumstance with inter-temporal dynamics and inter-regional features, as well as the existence of uncertainties from different markets due to GENCOs' bidding strategies and investment planning, electricity prices can feature with complex patterns. To develop a better forecasting tool to overcome the identified research challenges, a hybrid model based on PC and PF techniques is proposed in section 3.4. PCPF model is derived and illustrations are made to show how particle filter can be used to enhance the forecasting accuracy in day-ahead energy market price. After combining the advantages of both PC and PF, the proposed framework shows promising results in the comparisons with PC and other techniques in section 3.5.3.

CHAPTER 4. A NOVEL FRAMEWORK FOR REACTIVE POWER PROCUREMENT SCHEME

4.1. Introduction

A comprehensive framework has been developed to forecast electricity prices in an electricity market in chapter 3. This chapter is concerned with reactive power, another important aspect in electricity market planning and operation. Investigating the cost of providing reactive power service and establishing appropriate pricing structure are important both financially and operationally for reactive power procurement.

The importance and the difficulties of procuring and pricing reactive power in a competitive market environment have been illustrated in section 2.2.3. This chapter presents an algorithm for procuring reactive power from reactive resources based on a reactive power pricing structure. The role of reactive power is firstly analyzed in section 4.2, followed by a pricing structure of reactive power established in section 4.3. The concept of reactive power value based on the Equivalent Reactive Compensation (ERC) method is then introduced in section 4.4. Based on these analyses, a new algorithm of reactive power procurement is proposed in section 4.5, followed by a test of the proposed methodology on a classic 5-bus system in section 4.6. Summary of this chapter is provided in section 4.7.

4.2. Reactive Power Analysis

Adequate reactive power support and voltage regulation services are necessary for enabling active power transactions. In the deregulated structure of the electricity industries, the competitive provision of reactive power raises the need to optimally allocate reactive power requirements among existing plants.

Generally, reactive power support is divided into two categories: static and dynamic. Capacitors and inductors (or reactors) supply and consume static reactive power, respectively. They are called static devices since they have no active control of the reactive power output in response to the system voltage. Synchronous generators, synchronous condensers, Flexible AC Transmission Systems (FACTS) including static var compensators (SVC), static compensators (STATCOM), and Dynamic Var (D-var) are considered as dynamic reactive power devices capable of changing their output according to pre-set limits in response to the changing system voltages [46].

Beside those reactive support facilities, reactive power support from generators is regarded as an important ancillary service. The reactive power support of a generator has two roles or components. One helps to ship real power of generators, and the other improves the reliability of the system [173]. To improve system reliability, reactive power must be properly controlled to support the voltage. As reactive power can affect the voltage profile throughout a power system, it has a profound effect on the security of the system. Both voltage control and reactive-power management support reliability and facilitate commercial transactions across transmission networks. A generator supports the reliability of the system only after it produces adequate reactive power to cover its own need for shipping real power. The amount of reactive power needed by a generator to support the transmission of its own active power is defined as the minimum reactive power. It is a general consensus that the minimum reactive power should not be financially compensated.

A practical optimal power flow method, which is used to separate the minimum reactive power of generators with acceptable accuracy, is reported in [174]. The basic idea of the method is to minimize the total reactive power generations subjected to the equality constraints of the power flow equations and the inequality constraints of basic system operating constraints. The method can be expressed as follows:

$$
\begin{aligned}
&\min \sum_{i\in N_G} \left|Q_{gi}\right| \\
&s.t. \\
&P_{gi} - P_{li} - V_i \sum_{j\in N} V_j (G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}) = 0, && i \in N \\
&Q_{gi} - Q_{li} - V_i \sum_{j\in N} V_j (G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}) = 0, && i \in N \\
&\underline{Q}_{gi} < Q_{gi} < \overline{Q}_{gi}, && i \in N_g \\
&\underline{V}_i < V_i < \overline{V}_i, && i \in N
\end{aligned} \tag{4-1}
$$

where N and N_g are the set of all buses and all generators respectively, V_i represents the voltage magnitude at bus i, bus j connects to bus i, G_{ij} and B_{ij} are the real part and imaginary part of the element ij of the nodal admittance matrix, $\theta_{ij} = \theta_i - \theta_j$ is the voltage phase-angle difference between bus i and bus j, P_{gi} and P_{li} are the generator active power output and load active power level, Q_{gi} and Q_{li} are the generator reactive power output and load reactive power level, $\underline{V}_i$ and $\bar{V}_i$ are the lower and upper limits of V_i respectively, $\underline{Q}_{gi}$ and $\bar{Q}_{gi}$ are the lower and upper limits of Q_{gi} respectively.

The real power outputs of all generators, except the slack generator, are fixed. The slack generator serves to make good any losses in transmission. As a result, the real power flow pattern is obtained and the reactive power of a generator that is used to support its real power transmission can be studied. The control or optimized variables are the reactive power outputs of the generators. Solving this model, the total minimal reactive power support for the generators can be assessed. The following are the explanations of the model.

4.3. Reactive Power Pricing

Reactive power pricing is a fundamental and very important part of reactive power management. Analyzing the costs of reactive power service provisions and establishing an appropriate pricing structure are important both financially and operationally for the deregulated power industry. First, correct price signals are very important for facilitating transmission access and improving economic efficiency. With proper costing and pricing of reactive power, transmission users will have the ability to make decisions strategically on some economic activities such as energy transactions, investments, and asset utilization. Second, the operation efficiency and reliability of the power system concerned will be improved when well-balanced and appropriately distributed reactive power sources are available. Third, voltage profiles will be improved which, in turn, will reduce possibilities of incidents caused by high and low voltage problems, and even, voltage instability in some extreme cases.

An appropriate reactive power pricing structure is important both financially and operationally for a power market. First, it will facilitate transmission access and improve economic efficiency. Second, it will improve the efficiency and reliability of system operation. Last, it can deal with the voltage problem.

The cost of reactive power mainly includes reactive power capacity cost and production cost. Hence, reactive power pricing should cover both costs as follows:

$$B = B_c + B_u \tag{4-2}$$

where B is the reactive power price, B_c and B_u are the prices of the reactive power capacity cost and production cost, respectively.

A practical method is used to determine the unit cost of the reactive power capacity. In the method, a portion of the generator cost is allocated to the reactive power service. The portion is determined by the ratio of the reactive power output to the total power. Hence, the price function of the reactive power capacity cost is as follows:

$$B_c = \frac{p_u}{24 \times 365 \times y \times h} Q_g = kQ_g \tag{4-3}$$

where y is the life span (in year) of generator, h is the utilization rate, k is the price factor of reactive power capacity cost. Here, a portion of the generator capacity cost is allocated to the reactive power service. Mathematically, p_u is given by:

$$p_u = TIC \tan(\cos^{-1}(\text{p.f.})) \tag{4-4}$$

where TIC is the total installation cost of the generator, p.f. is the rated power factor of the generator. The aim of employing the power triangular relationship among kVA, kW and kVAr to derive equation (4-4) is to separate the costs associated with the real and reactive power, respectively. Notice that different pricing methodologies have different advantages and disadvantages. Different electricity markets may use different methods for reactive power pricing. In some cases capacity cost is recovered through availability payments or fixed annual amount. However, the major advantage of using linear functions in this chapter is that it is a more equitable approach.

Based on the classification of the roles of the reactive power production, using similar approach presented in [175], the pricing function of the reactive power production cost is shown in Fig. 4-1. Mathematically, it is represented as:

$$B_u = \begin{cases} mQ_g & \underline{Q_g} \le Q_g \le 0 \\ m'Q_g & Q_{gm} \le Q_g \le Q_{ga} \\ c + bQ_g + aQ_g{}^2 & Q_{ga} \le Q_g \le \overline{Q_g} \\ 0 & otherwise \end{cases} \tag{4-5}$$

where *m, m', a, b* and *c* are constants [175]. Q_{gm} is the amount of reactive power needed by the generator to support the transmission of its own active power; Q_{ga} is the reactive power output of the generator above which active power generated needs to be reduced to adhere to winding heating limits of the generator.

It should be noticed that the reactive power output from 0 to Q_{gm} is for shipping the real power output of the generator. Therefore, reactive power output in this region is not qualified as an ancillary service and the generator is not entitled for any payment.

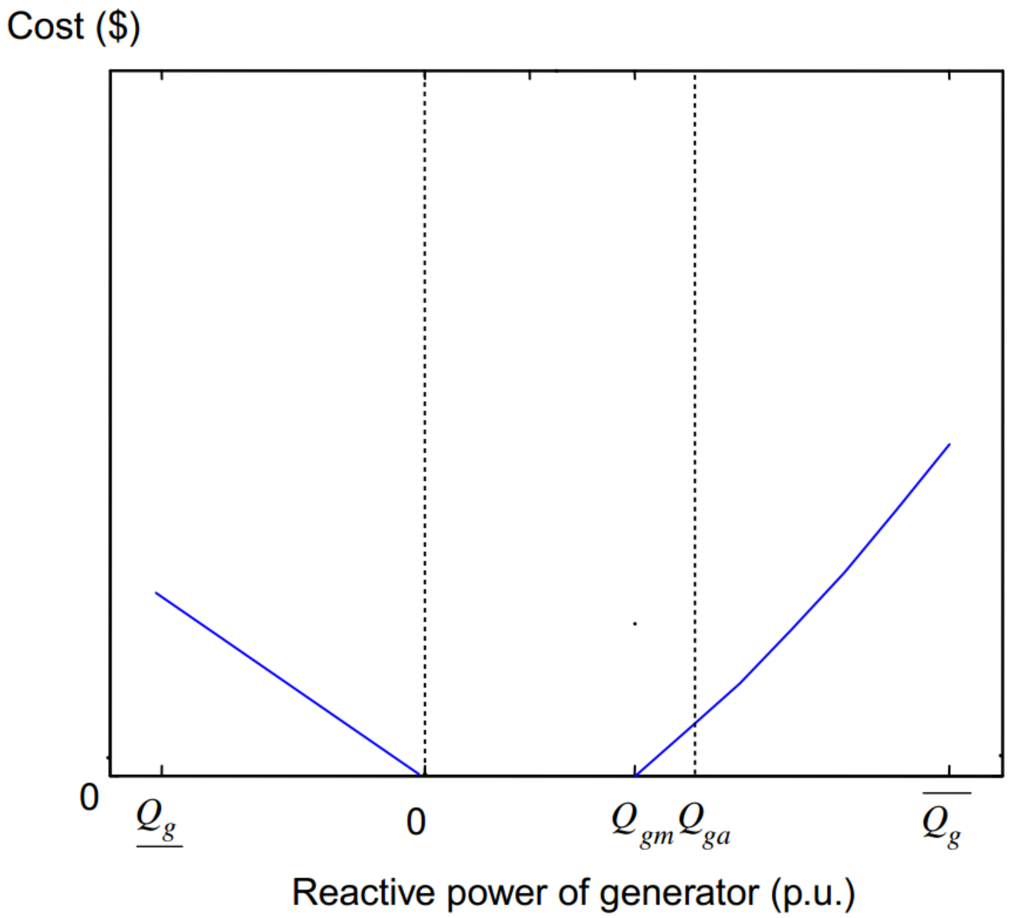

Fig. 4-1 Price function of reactive power production cost

4.4. Reactive Power Value

Because reactive power needs to be provided locally, a reactive source could have a high cost but a low value. It relates to the system configuration and operation conditions, location of each source etc. Hence the relative importance of the reactive power sources needs to be measured. The reactive power value can offer a correct signal to providers and ensure power system security. The equivalent reactive compensation (ERC) method [49] is a useful and practical method to evaluate the reactive power value.

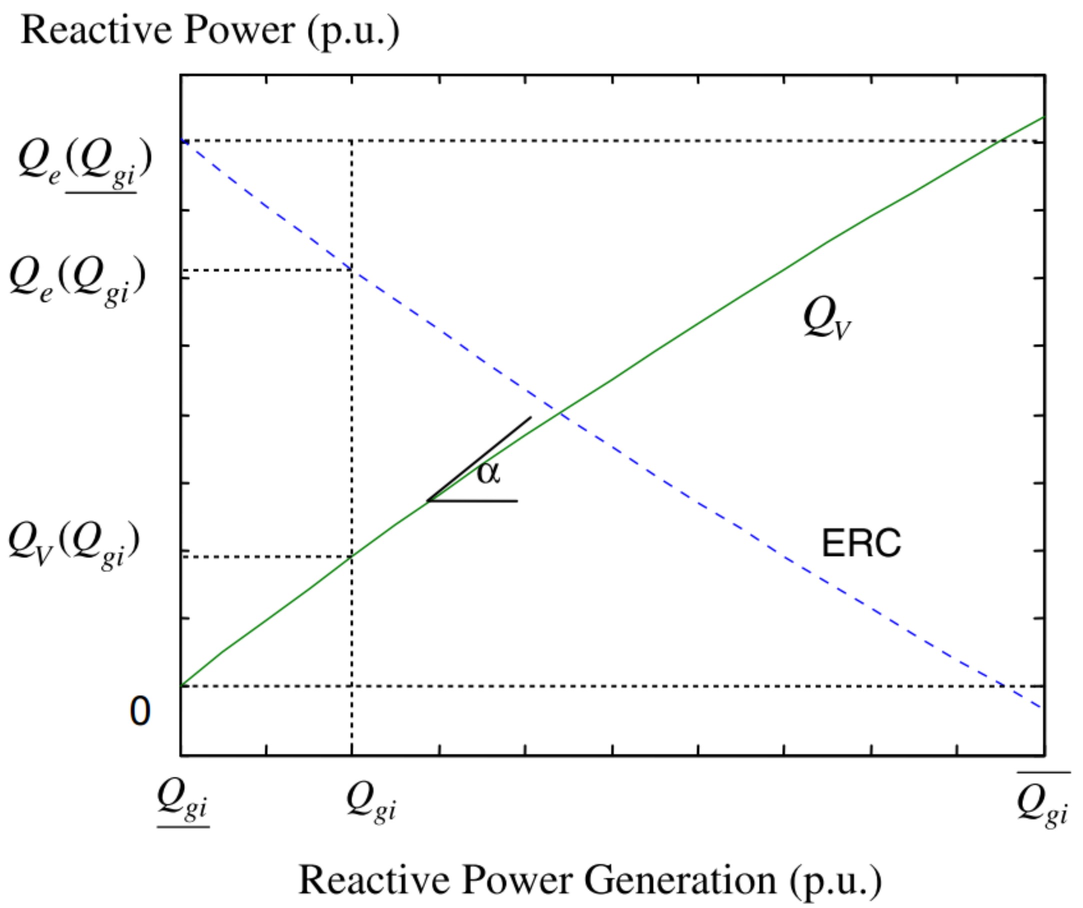

Fig. 4-2 Value factor of reactive power

The basic concept of the ERC method is keeping the same system status by replacing a reactive power resource with other compensating reactive power resources. If a reactive power source reduces its output, the system status will change. To maintain the same system status, reactive power compensations must be added to the system. The total amount of compensation is an indicator of the reactive power value. Based on the ERC method, value factor is proposed in this chapter to measure the reactive power value. The procedure to calculate the reactive power value factor is as follows:

A. Select a typical system condition and establish a solved case.

B. Fictitious condensers are used as the compensation tools. They are added to each load bus. The original and limit reactive power values of the fictitious condensers are set to zero and infinite, respectively.

C. Hold the reactive power output of all reactive power sources at the base case levels. To find the base case levels, a power flow is run on a typical system condition.

D. Select a reactive power source and set its active power output zero. The inequality active power is shared by the rest of the power sources based on an Optimal Power Flow (OPF) solution. The OPF also provides the reactive power outputs of the generators. Its reactive power output Q_{gi} is varied from zero to its limit. For each reactive power output, sum up the total reactive power output $Q_e(Q_{gi})$ of all the fictitious condensers. The ERC curve can thus be constructed as shown in Fig.4-2.

E. Using the equivalent reactive compensation, the reactive power value curve can be constructed as follows:

$$Q_v(Q_{gi}) = Q_e(\underline{Q}_{gi}) - Q_e(Q_{gi}) \tag{4-6}$$

Where $Q_v(Q_{gi})$ is the reactive power value when the reactive power source output is Q_{gi}.

F. The slope, tanα, of value curve at the base case level is used as the reactive power value factor e.

G. Repeat Steps d) to f) for all the reactive power sources of interest.

If system contingencies are considered, the impact of the contingencies on reactive power support valuation should be carried out. A possible approach to deal with the problem is as follows: Each line contingency case is taken as a new case. The compensations and value curves for the contingency cases are obtained as the procedure outlined above. A combined value curve for application in different operating scenarios can then be constructed as a weighted summation of all the value curves for each studied generator.

4.5. Reactive Power Procurement

Reactive power service is a key type of system support in competitive market. The problems faced by system operators in its provision mainly arise due to the integration of costing of this service with technical aspects. Generators as key sources for providing dynamic reactive power are individual entities in competitive electricity market and appropriate procurement of generator reactive power would lead to more secure and efficient operation of power system. This would be achieved by considering the effects of reactive power on system operation. In this chapter, value based as well as the cost based procurement aspects would be incorporated.

The value of reactive power is not only dependent on the cost, but also related to other factors such as location.Valuation of reactive power support services should be based on their contributions to system security and stability. There are many factors that can affect the valuation of reactive power support and it is difficult to quantify their relative importance without a proper methodology and associated algorithms. The results should lead to a market signal on the location and extent for reactive support service needs. The quantitative index described in section 4.4, representing the value of the reactive power output of each generator, is used as a weighting factor in the optimization problem described in equation (4-7). In addition to considering the cost of reactive power transportation and generation, the value of reactive power is also taken into account.

$$
\begin{aligned}
&\min F = \sum_{i=1}^{N_G} B(Q_{gi}) / e_i \\
&s.t. \\
&P_{gi} - P_{li} - V_i \sum_{j \in N} V_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) = 0, && i \in N \\
&Q_{gi} - Q_{li} - V_i \sum_{j \in N} V_j (G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij}) = 0, && i \in N \\
&\underline{Q}_{gi} < Q_{gi} < \overline{Q}_{gi}, && i \in N_g \\
&\underline{V}_i < V_i < \overline{V}_i, && i \in N
\end{aligned}
\tag{4-7}
$$

Similar to real time pricing of active and reactive power, the determination of the reactive power value and the setting of the procurement of reactive power in this chapter are determined for the system operating conditions at a particular time. It is sensitive to the system constraints and operation conditions. Primal dual interior point method [176] is employed to solve the nonlinear programming problems.

Note that the procurement of reactive power is determined for the base case conditions and hence in this chapter *e* is chosen as that evaluated in the base case condition. However, as the operating point of the generator changes, there will be slight changes in the value of *e*. If high accuracy is required, an iterative approach to determine the value of *e* will be suitable. Based on reactive power output of the reactive power sources obtained in the solution of equation (4-7), the reactive power value factors *e* can be re-evaluated as described in section 4.6. The iterative process is continued until there are no variations of the reactive power value factors.

4.6. Experiment on The Proposed Model

A commonly adopted 5-bus test system [49] for reactive power studies as depicted in Fig.4-3 is used to illustrate the reactive power procurement method proposed in this chapter. There are three generators, namely G_1, G_2 and G_3, feeding a load center at bus 5. There is a distant slack generator G_4 that supplies little power to the load but serves as a reference to the system. The active load is shared equally by generators G_1 to G_3. All parameters are in per unit and their values are depicted in the figure.

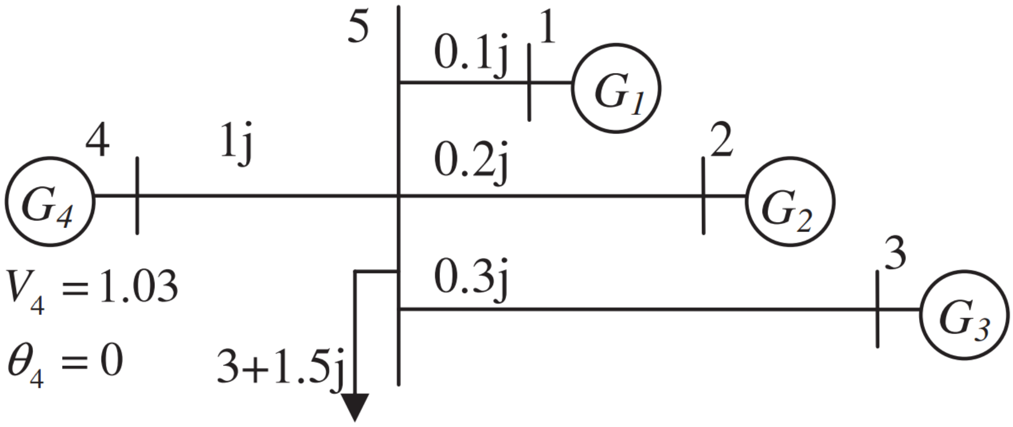

Fig. 4-3 The 5-bus test system

Table 4-1 Generator minimum reactive power

Generator	***Minimum reactive power***
G_1	0.1630
G_2	0.1928
G_3	0.2145

Table 4-2 Generator output

Generator	***Active***	***Reactive***
G_1	1	1.1135
G_2	1	0.6400
G_3	1	0.5216
G_4	0	0.1059

Table 4-3 Bus voltage

Voltage	***Magnitude***	***Phase***
V_1	1.01	0.1047
V_2	1.01	0.2106
V_3	1.01	0.3190
V_5	0.9052	0

Based on equation (4-1), subjected to the equality constraints of the power flow equations and the inequality constraints of basic system operating constraints, the amounts of minimum reactive power from generators G_1 to G_3 are calculated and listed in Table 4-1.

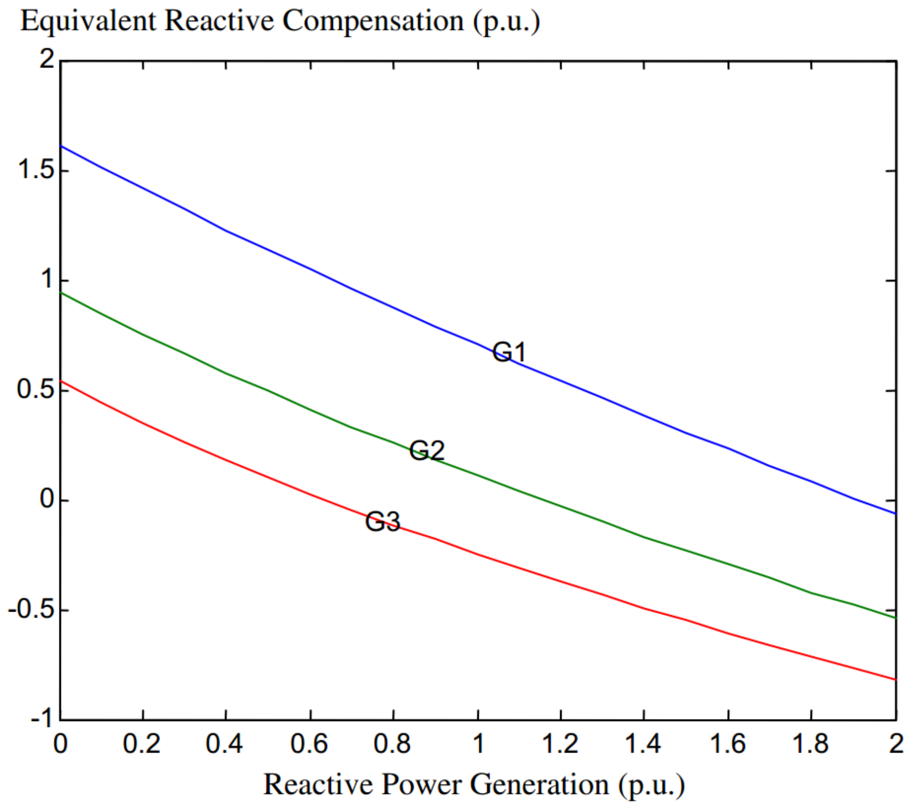

Fig. 4-4 Equivalent reactive compensation

To obtain the reactive power value factor, first a power flow is run. The base case results (in p.u.) are listed in Tables 4-2 and 4-3. Due to the local nature of the reactive power, the results obtained in Table 4-2 are that the nearest generator to the load, G_1, produces most of the reactive power while the remotest generator to the load, G_4, produces the least reactive power. A fictitious condenser is added to bus 5 in this case. The ERC method is used to plot the equivalent reactive compensation and the reactive power value as shown in Fig.4-4 and Fig.4-5, respectively. To obtain Fig 4-5, a base case should be solved first. The reactive power generation curves as a function of the reactive power value are then plotted one by one. The slopes of the reactive power value curves at the base case level are calculated as the reactive power value factors. The reactive power value factors are listed in Table 4-4.

Table 4-4 Value factor of reactive power

Generator	***Value factors***
G_1	0.8200
G_2	0.7900
G_3	0.7530

For the purpose of clear illustration of the performance of the proposed reactive power procurement methodology with reactive power value taken into account, it is assumed that the generators operate on the limiting part of the loading capability curve when generating Qgm, i.e. Qga coincides with Qgm. With the coefficients of the price functions of capacity cost and production cost listed in Table 4-5, Equation (4-7) is solved to obtain the amounts of reactive power procurement. The results (in p.u.) are listed in Table 4-6.

Table 4-5 Bidding parameters

Generator	***Capacity***	***Production***			
	k	*m*	*a*	*b*	*c*
G_1	500	-160	120	100	15
G_2	600	-180	100	150	20
G_3	700	-170	110	120	10

Table 4-6 Amounts of reactive power procurement

Generator	***Procurement***	
	Without e	**With** e
G_1	1.0959	1.1116
G_2	0.6275	0.6079
G_3	0.5087	0.5142

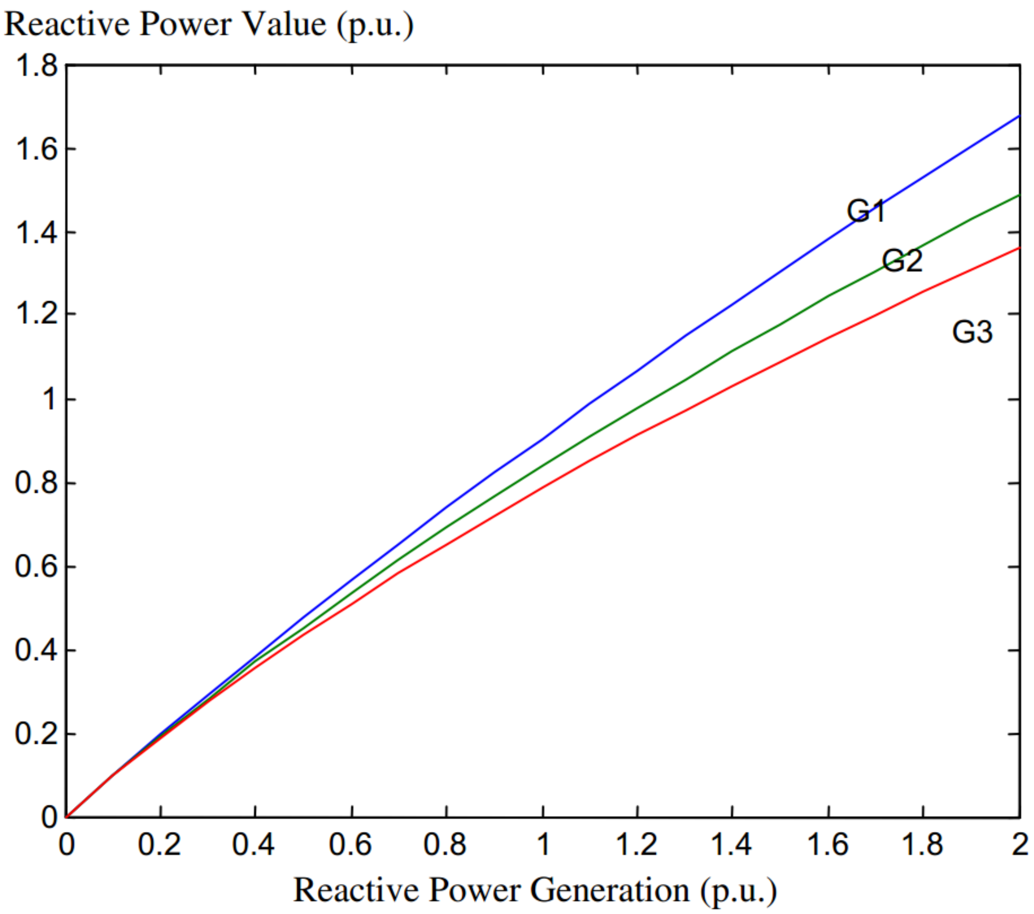

Fig. 4-5 Reactive power value of generators

From Table 4-6, it can be observed that the nearest generator to the load, G_1, produces most of the reactive power. Consider the reactive power value factor e taken into account. The reactive power value factor of generator G_1 is the highest, so the procurement amount increases. However, generator G_2 produces less reactive power and G_3 produces more reactive power even G_2 has a higher reactive value factor. The reason is that the price of generator G_2 reactive power is much higher than that of generator G_3. Hence it can be observed that the method proposed in this chapter takes into account reactive power capacity and production cost as well as reactive power value.

4.7. Summary

Deeper deregulation in power supply industry has made reactive power management a critical task to power system operators from both technical and economic perspectives. Chapter 4 proposes a practical market-based reactive power management scheme to tackle the challenge. The roles and cost, as well as price structure, of reactive power are addressed in sections 4.2 and 4.3, respectively. The assessment of the relative importance of different reactive power sources is developed and the value factor is introduced for reactive power valuation in section 4.4. An equitable and novel method of reactive power procurement in an open access environment is presented in section 4.5. The algorithm takes into account reactive power capacity and production cost as well as reactive power value. Experiment on the commonly used 5-bus test system for reactive power studies in section 4.6 show the feasibility and validity of the algorithm.

CHAPTER 5. IMPACTS OF EMISSION TRADING SCHEMES ON GENCO'S DECISION UNDER MULTIMARKET ENVIRONMENT

5.1. Introduction

As discussed in section 1.3, this thesis aims at developing novel frameworks for electricity market planning and management. Chapters 3 and 4 proposed novel pricing models for both real power and reactive power. These proposed methods are useful for investigating a GENCO's decision making either in this chapter or the following chapters. Following the research route depicted in section 1.5, Chapter 5 is dedicated to propose a novel dynamic decision making model to deal with the multimarket trading problem for a GENCO during each trading period. As discussed in section 2.4.1, the implementation of ETS has significant influences on GENCOs' operation for either short term or long term. Based on the novel forecasting method developed in chapter 3, the proposed model enables a GENCO to make a rational trade-off between profit-making and emission reduction under the three interactive markets environment. Besides the forecasting method, Differential Evolution (DE) is employed to solve the multi-period stochastic optimization problem and give the optimum results for each time interval. This chapter covers electricity market, carbon market and fuel market and contributes for a comprehensive short term electricity market planning model.

Electricity industry worldwide has been deregulated on the generation and retail sides; as such there are two major changes: (i) generation companies (GENCOs) are free to operate and compete in the market. (ii) GENCOs are subject to competition in the electricity market (EM). The model proposed in this chapter builds upon the EM consisting of a power pool and bilateral trades [177]. The primary goals of EM are to provide energy securely, reliably and efficiently. While EM usually meets these goals, other valued outcomes, including conserving finite resources, maintaining stable and reasonable electricity cost, and protecting the environment, are at the stakes.

To address these problems, policies such as Emissions Trading Scheme (ETS) have been adopted to mitigate the emission by market-based mechanisms. Under this scheme, specified amounts of emission allowances are allocated to various industrial installations, including generators. These allowances can be used either for producing corresponding amounts of CO_2 or trading in Carbon Market (CM). If the total emission over the emission commitment period (which is the period within which a country/region must remain the national/regional emission level specified by its target) exceeds the allocated allowances, a GENCO has to either purchase allowances from a carbon market or pay a penalty. A GENCO's stock of allowances is composed of two parts: initial allowance (allocated freely) and purchased allowance (trade or auction from a carbon market). Generally, initial allowances are assigned to a GENCO annually through grandfathering, output-based allocation or an auction based method. Output-based allocation does not require the entities to pay for the allowances. Entities would be allocated an amount of allowances proportional to their current production. More detailed discussions can be found in section 2.3.3. Reference [178] indicated that EM would be affected by the scheme. On the one hand, electricity prices would be affected by the scheme as GENCOs seek to pass their additional cost to consumers. Operational decisions of GENCOs on electricity production and related fuel portfolio would also be affected significantly. The deregulation of EM and the implementation of CM require each GENCO builds up its own fuel portfolio according to the prices variation in Fuel Market (FM). In the long run, GENCOs therefore have to contract their fuels in an optimal way that allows them to operate in the multimarket environment without incurring any negative profits. In the daily operation, GENCOs have to decide the usage of their fuel according to the production with consideration of different fuel prices.

The problem addressed in this chapter is that separate and evolving public policy debates are currently shaping EM, CM and FM without paying attentions to how each market affects the others, yet GENCOs are subject to the influences from the three interactive markets. Without a better understanding of how a GENCO would react to these three markets, it is difficult to design policies which can achieve the environmental and economic societal goals. To address the value of different market mechanisms, this chapter proposes a dynamic decision making model for GENCOs to deal with the multimarket trading problems in each trading interval. In section 5.2, several important issues relating to the proposed model are explained, followed by the model formulation described in section 5.3. section 5.4 describes the solution of the proposed model. In section 5.5, comprehensive experiments are presented to compare the multimarket performances under different scenarios. Finally, section 5.6 summarizes this chapter.

5.2. Problem Formulation

To take the uncertainties of EM, CM and FM into account, this chapter proposes a two-stage decision making model to give the optimal results in both production process and trading process. Furthermore, another major motivation of the chapter is to investigate how different market mechanisms affect decisions of a GENCO. The reason is that a GENCO's decision on how to make use of the generators, the corresponding fuels as well as the allocated emission allowances would be different under different market environments.

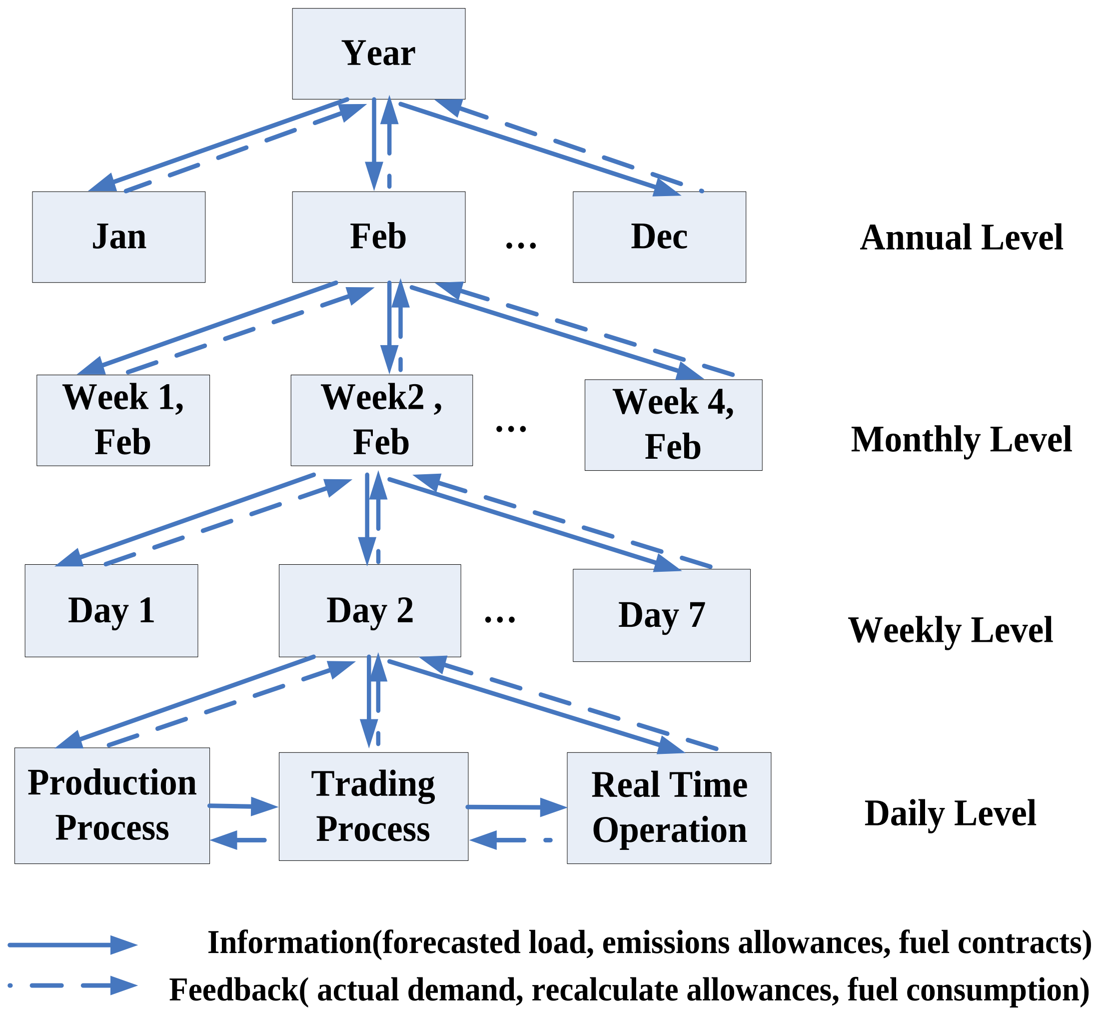

Fig. 5-1 Hierarchical decision making model

A multi-time period electricity network optimization model was presented in [179], which took gas flows, price and storage problem in FM into account, for GENCOs. Reference [180] presented a dynamic economic emission dispatch model of power systems, which included a handling scheme to deal with emission constraints. A typical environmental/economic power dispatch optimization problem was described in [181], which included fuel cost minimization and emission constraints. However, these studies did not take into account the effects of emission trading. The existing literatures treated emission allowance as a fixed cost so that the trading value had been ignored. So far there is no literature addresses the optimal decision making of GENCOs with the effects of EM, FM and CM taken into account.

In contrast to the works that consider only caps on emission, the model proposed in this chapter solves the decision making problem by maximizing the total profit of a GENCO in the entire planning period. This is a complex decision making problem in which all units have to be scheduled to satisfy not only power demand of bilateral trades and power pool but also spinning reserve of the system. Furthermore, the trading in the three interactive markets has to be coordinated with environmental constraints. In order to simplify the illustration and highlight the characteristics of the model, all the units are assumed to be online during the whole planning period. However, it should be noted that unit commitment can be integrated into the proposed model easily. As shown in Fig.5-1, the decision making model decomposes the scheduling problem into a hierarchical structure.

5.2.1. Hierarchical decision making model

The proposed decision making model enables a GENCO to maximize its profit through proper decision making in a hierarchical structure. Without loss of generalities, all units of a GENCO are assumed online during the planning period. However, the unit commitment that actually determines the on-off status of units can be integrated into the proposed model easily. At each planning level, a GENCO's total expected output is forecasted based on the corresponding historical data using forecasting methodology PC proposed in chapter 3. Then the forecast output can be equally spread to each time span of its sublevel (termed as average dispatch). As a result, necessary information of the sublevel including fuel consumptions and emissions can be obtained. On one hand, the average dispatch at the higher levels helps a GENCO to make a rational decision under multimarket environment to benefit the long term interests in planning market operations and new investments etc. On the other hand, the average dispatch provides useful information at the lower level. For instance, at the daily level, a daily allocated emission allowance is established through the average dispatch at the weekly level. In this manner, the decision model can include emission constraints that accounts for the maximum allocated allowances as well as possible trades in the carbon market. The differences between the planning (production process and trading process) and the operation in real time are used to update information in the next planning period at each level. Although the model can be applied for both long and short term planning, this chapter focuses on the short term decision making in market operations only.

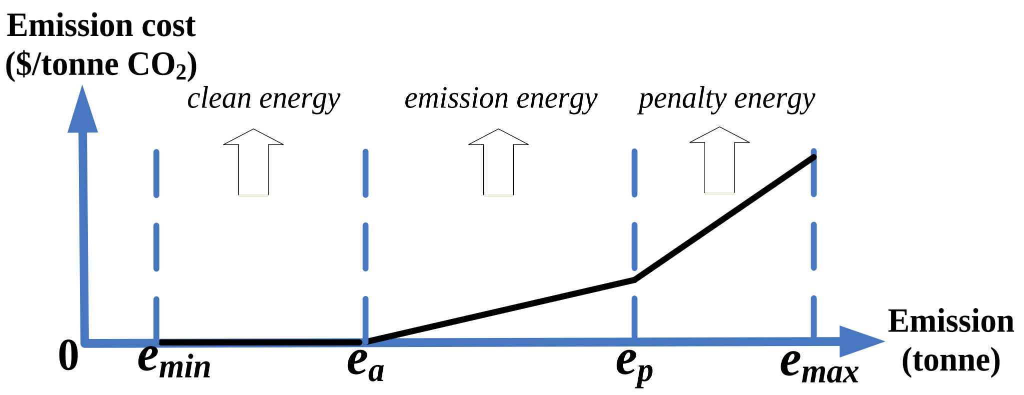

Fig. 5-2 Piecewise emission cost of three parts of energy

There are two sequential processes at the daily planning level which interact each other through the stock of carbon allowance. Based on the updated stock of carbon allowance, the proposed model solves the optimal electricity production by DE subject to environmental and economical constraints from EM, FM and CM in the production process. It is followed by the trading process. In the trading process a GENCO not only has to maximize its trading profits but it also needs to balance the allowances with the produced emissions by the end of the planning horizon in the most cost-effective way. As either stage can directly change the GENCO's stock of carbon allowance, the piecewise emission cost shown in Fig.5-2 will therefore change dynamically. To take into account of this complicated problem, the proposed model innovatively considers the emission as a dynamic constraint in optimizing the decision in each market.

The *clean energy* is the generated energy using the daily allocated allowance a GENCO owns. Therefore, the "clean energy" contributes to the amount of emission but requires no additional cost for the GENCO. The *emission energy* is produced beyond the daily allocated allowance; therefore, a GENCO must purchase allowances from CM to cover it. The *penalty energy* represents the energy production without any allowances and hence every unit of emission will be penalized. As all the units are assumed to be available in the whole planning period $d = \{d_0, D\}$, $e_{\min}$ and e_{max} is the lowest emission and maximum emission according to their production, respectively. e_a and e_p are the two emission thresholds varying according to the transactions in CM and the GENCO's production. The two thresholds can be considered as dynamic constraints in the decision making model. The emission cost on day d, $C_d^{co_2}$, is therefore represented by the following piecewise function:

$$C_d^{co_2} = \begin{cases} 0 & \sum_{t=1}^{24}\sum_{g=1}^{G} e_g(q_{d,t,g}) \le e_a \\ \left(\sum_{t=1}^{T}\sum_{g=1}^{G} e_g(q_{d,t,g}) - e_a\right) p_d^{CM} & e_a < \sum_{t=1}^{24}\sum_{g=1}^{G} e_g(q_{d,t,g}) \le e_p \\ e_p p_d^{CM} + \left(\sum_{t=1}^{T}\sum_{g=1}^{G} e_g(q_{d,t,g}) - e_p\right) p_C^{PP} & e_p < \sum_{t=1}^{24}\sum_{g=1}^{G} e_g(q_{d,t,g}) \end{cases} \quad (5\text{-}1)$$

where $e_g(q_{d,t,g})$ is the emission function due to the production of generator g. A GENCO usually has different types of generators and its daily emission is the sum of emissions of all its generators within T time intervals. Notice that the penalty is usually settled at the end of the emission commitment period (i.e. on the compliance day C). It is obvious that any trades in CM and any production of emission would directly change the stock of carbon allowances and hence e_a and e_p would vary accordingly while the allowances a GENCO can acquire from CM are stochastic depending on the market setting. In this chapter, historical trading data in previous commitment periods are fitted into a lognormal distribution at the long term levels, i.e. annual and monthly. The maximum amount of allowances a GENCO can acquire from CM during the commitment period is firstly obtained using the Monte Carlo technique with a given level of risk before the planning period. Then the total estimated allowances, including allowances which have been allocated and purchased as well as allowances which a GENCO can possibly purchase from CM, are averagely dispatched to the monthly or weekly level as shown in Fig. 5-1.

5.2.2. Energy production of a GENCO

Under the deregulated market environment, a GENCO has to decide the amount of power generation by considering two components. One is long term bilateral contracts while the other is power pool. Usually the long term bilateral contracts are confirmed at the high levels planning. Power pool features with fluctuated price and stochastic demand, a GENCO has to make a trade-off between profit and risk of low actual energy price. Therefore, a GENCO's output $\sum_{g=1}^{G} q_{d,t,g}$ at time interval t on day d is represented by bilateral contracts and power pool parts $d_{d,t}$ and $\omega_{d,t}$, respectively.

Due to uncertainties involved e.g., in market clearance, the determination of optimal volumes of the two parts is a challenging task for GENCOs. In a power pool, the power pool prices are cleared through a complex balancing process. Although the prices are highly volatile, a GENCO can develop its optimal bidding price and output in a power pool according to the forecast price. Furthermore, a GENCO has to decide the trading in the three markets simultaneously. To obtain the optimal energy production for each time interval, the production process of the proposed model firstly forecasts the maximum possible output $\lambda_{d,t}$ in the power pool based on given known information of historical market prices using PC described in Section 3. Subject to the constraints in the three markets, Differential Evolution (DE) is then applied to decide the optimal energy production $d_{d,t} + \omega_{d,t}$, along with the $q_{d,t,g}$ dispatched to all units. It is noticed that the optimal volume of electricity output is determined with the bidding price simultaneously. To focus on the planning considering the three markets, the production process provides the best $(\omega_{d,t}, q_{d,t,g})$ as the decision in EM so as to enable the trading process to deal with the trading strategies in FM and CM.

5.2.3. Carbon allowance trading

A GENCO must balance its emission allowances with the generated emissions at the end of the emission commitment period. On the last day of the emission commitment period (i.e. compliance day *C*), GENCO must pay a penalty price for excessive emissions without allowance as follows (on day C, $c_d^S = c_C^S$, $c_d^B = c_C^B$, $x_d = x_C$, $q_{d,t,g} = q_{C,t,g}$):

$$Penalty_C = p_C^{pp} \max[(\sum_{t=1}^{T}\sum_{g=1}^{G} e_g(q_{C,t,g}) + c_C^S) - (x_C + c_C^B), 0] \tag{5-2}$$

where x_C, and $\sum_{t=1}^{T}\sum_{g=1}^{G} e_g(q_{C,t,g})$ are the stock of carbon allowances and the accumulated emission at the beginning of day *C* respectively; c_C^B, c_C^S are units of carbon allowances buying and selling on day *C*. The penalty price p_C^{pp} is determined before the commitment period based on the national/regional emission cap as introduced in section 2.3.1. To avoid penalty, a GENCO can either operate their units subject to the initial allowances or purchase additional allowances in CM before day *C*.

5.2.4. Prices of fuel, energy and carbon allowance

According to the discussion in Section 2.4.1, a GENCO can hardly affect the market clearing prices in the short term. Therefore, the proposed model considers the market prices as exogenous variables in the low level planning. The predicted value of fuel price $p_{d,t,g}^{FM}$, energy price $p_{d,t}^{PEM}$ and the carbon allowance price p_{d}^{CM} are important to the performance of the proposed decision making model. E.Delarue [182] has demonstrated that the bias of prices forecasting would lead to different extends of GENCO's profit loss. In this chapter, the predicted spot prices of fuel, energy and carbon allowance are known before planning using the PCPF model proposed in chapter 3.

5.2.5. Differential Evolution (DE)

The proposed model is a mix-integer programming problem. It consists of both continuous variables such as generation outputs, and discrete variables such as contract amounts. Although the model is not highly nonlinear, it is a NP-hard problem. For such NP-hard problems, traditional algorithms (such as the branch-bound programming method, dynamical programming method, mixed integer programming method, Lagrangian method) may converge to a feasible solution in a reasonable execution time, but they cannot guarantee good accuracy of the final solution due to the assumptions involved in these methods. Therefore, by considering the strong searching ability of the heuristic algorithms, DE, with better quality and reasonable convergence speed, is adopted to find the solution. DE can be used to solve stochastic problems effectively [183]. It resembles the structure of an Evolution Algorithm (EA), but differs from traditional EA in its generation of new candidate solutions and by its use of a 'greedy' selection scheme. DE has the following steps: initialization, mutation, crossover, and selection. In the initialization step, each of

N individuals is a P dimensional vector within the whole population Π of dimension $N\times P$. The structure of the whole population is shown as:

$$[\Pi]=\begin{bmatrix}\Pi_{11} & \Pi_{12} & \dots & \Pi_{1P}\\ \Pi_{21} & \Pi_{22} & \dots & \Pi_{2P}\\ \vdots & \vdots & \vdots & \vdots\\ \Pi_{N1} & \Pi_{N2} & \dots & \Pi_{NP}\end{bmatrix} \tag{5-3}$$

DE randomly generates the value of each dimension of the individual within the lower and upper limits of that dimension. The objective of the mutation process is to randomly choose three different individuals to produce a mutant individual $V_{j,k,l}$, according to $V_{j,k,l}=X_{j,a,l}+F\left(X_{j,b,l}-X_{j,c,l}\right)$, where j is the dimension index, k is individual index and l is iteration index. a, b, c are random numbers within [1, N]; F is the mutation factor.

In the crossover step, DE creates a different individual called the trial individual, based on the original individual $X_{j,k,l}$ and the mutant individual $V_{j,k,l}$. The crossover is expressed as:

$$U_{j,k,l}=\begin{cases}V_{j,k,l} & if\ rand_j\left(0,1\right)\le Cr\ or\ j=j_{rand}\\ X_{j,k,l} & otherwise\end{cases} \tag{5-4}$$

where Cr is the mutation factor.

The last step is selection where DE produces individuals for the next iteration. The original individual and the trial individual are compared using their objective function values. The one with the larger value is selected for the next iteration. The three steps (mutation, crossover, and selection) repeat until an acceptable solution is obtained or the predefined maximum iteration number is reached.

5.3. Model Formulation

The profit of a GENCO during the whole planning period $d=\{d_0,\ D\}$ is the revenue from EM, FM and CM minus the total production cost and expense. The profit can be expressed as follows:

$$\Gamma_D=(R^{BEM}+R^{PEM}+R^{CM}+R^{FM})-(C^{CM}+C^{LFM}+C^{FM}+C^{PEM}) \tag{5-5}$$

5.3.1. Revenue from long term bilateral energy contracts

In EM, the revenue of a GENCO comes from the bilateral contracts and the power pool. Assume a GENCO has I long term bilateral energy contracts. Each contract i consists of the capacity part (which reserve the GENCO's capacity to provide power) and the energy part. Each part corresponds to a specified contract price $p_{d,t}^{CC}$ and $p_{d,t}^{EC}$, respectively. The revenue from the bilateral contracts R^{BEM} is represented as:

$$R^{BEM}=\sum_{d=d_0}^{D}\sum_{t=1}^{T}\left[P_{d,t}^{CC}\sum_{i=1}^{I}Q_{d,t,i}+P_{d,t}^{EC}\sum_{i=1}^{I}\min\left(l_{d,t,i},Q_{d,t,i}\right)\right] \tag{5-6}$$

where $l_{d,t,i}$ is the predicted load of the customer and $Q_{d,t,i}$ is the capacity of bilateral contract *i* at time interval *t* on day *d.*

5.3.2. Revenue from trading in power pool

The revenue from selling electricity in the power pool R^{PEM} is another income of a GENCO. The proposed model solves the optimal power production $q_{d,t,g}$ using DE and therefore its revenue is

$$R^{PEM}=\sum_{d=d_0}^{D}\sum_{t=1}^{T}\left\{p_{d,t}^{PEM}\max\left[\sum_{g=1}^{G}q_{d,t,g}-\sum_{i=1}^{I}\min\left(l_{d,t,i},Q_{d,t,i}\right),0\right]\right\} \tag{5-7}$$

where $l_{d,t,i}$ is the predicted load of the customer and $Q_{d,t,i}$ is the capacity of bilateral contract *i* at time interval *t* on day *d.*

5.3.3. Revenue from trading in CM

Besides balancing the emission, a GENCO would aim for profits from the trading of carbon allowances. The proposed model optimizes the trading amount of allowance in carbon market, with the consideration of variation in the emission level and the allowance price. It is computed as:

$$R^{CM} = \sum_{d=d_0}^{D} \left(I_d^{CMS} p_d^{CM} c_d^S \right) \tag{5-8}$$

Excessive trades are limited through the index I_d^{CMS} which takes the allowance price variation into account:

$$I_d^{CMS} = \begin{cases} \beta, & if \ \dfrac{\mu(p_{d+1:D}^{CM}) - p_d^{CM}}{p_d^{CM}} < r_1 \\ 0, & if \ \dfrac{\mu(p_{d+1:D}^{CM}) - p_d^{CM}}{p_d^{CM}} \geq r_1 \end{cases} \tag{5-9}$$

where $\mu(p_{d+1:D}^{CM})$ is the mean value of the allowance price from day d+1 to day D, which is forecasted by the methodology proposed in reference [184]; β is the penalty factor within [0, 1]; r_1 is the risk factor of a GENCO within [0, 1], which is used to control excessive selling.

5.3.4. Revenue from trading in FM

To guarantee the supply of fuel for different types of generators, a GENCO usually would own a certain amount of fuel contracts. However, when a GENCO has surplus of fuel in some days it would resell part of the contracts in fuel markets to avoid extra storage cost. To include the impact of fuel market externalities and simplify the discussion of the model, all the trades in FM are assumed to be similar to the gas market. Therefore, no storage problems are considered in the study.

$$R^{FM} = \sum_{d=d_0}^{D}\sum_{t=1}^{T}\sum_{g}^{G}\left[p_{d,t,g}^{FMS} \max\left(Q_{d,t,g}^{FM} - f_g(q_{d,t,g}), 0\right)\right] \tag{5-10}$$

where $Q_{d,t,g}^{FM}$ is the long term fuel contract heat energy amount of generator g at time interval t on day d, which is settled in the high level planning; the sale price, $p_{d,t,g}^{FMS}$, is calculated based on the predicted benchmark price $p_{d,t,g}^{FM}$ of the fuel market: $p_{d,t,g}^{FMS} = \beta p_{d,t,g}^{FM}$. Similar to [20], the fuel consumption function of generator g can be expressed as: $f_g(q_{d,t,g}) = a_g + b_g q_{d,t,g} + c_g q_{d,t,g}^2$, where a_g, b_g, c_g are fuel consumption parameters of generator g.

5.3.5. Cost of trading in CM

In each trading process, a GENCO, if necessary, can purchase emission allowance when the allowance price in the carbon market p_d^{CM} is relatively low. It this case, the cost of a GENCO in CM is:

$$C^{CM} = \sum_{d=d_0}^{D}\left[I_d^{CMB} p_d^{CM} c_d^{B} \right] \tag{5-11}$$

The allowance buying index I_d^{CMB} suggests purchasing allowances when the current price is lower than the mean value of the future prices at a certain level, which is expressed as follows:

$$I_d^{CMB} = \begin{cases} \beta^{-1}, & if\ \dfrac{\mu(p_{d+1:D}^{CM}) - p_d^{CM}}{p_d^{CM}} > r_1 + r_2 \\ 0, & if\ \dfrac{\mu(p_{d+1:D}^{CM}) - p_d^{CM}}{p_d^{CM}} \le r_1 + r_2 \end{cases} \tag{5-12}$$

where the risk factor r_2 is used to control excessive purchasing.

5.3.6. Cost of long term bilateral fuel contracts

The price of the long term fuel contract for generator g, which is known before the planning period, is $P_{d,t,g}^{LFM}$. Hence, in fuel markets, the total cost of the long term contracts, C^{LFM} , can be expressed as follows:

$$C^{LFM} = \sum_{d=d_0}^{D} \sum_{t=1}^{T} \sum_{g=1}^{G} \left[P_{d,t,g}^{LFM} Q_{d,t,g}^{FM} \right] \tag{5-13}$$

5.3.7. Cost of trading in FM

A GENCO needs to purchase fuel to meet the demand of the generators when the amount of fuel related to the long term contract is not sufficient. The cost of fuel purchasing C^{FM} is expressed as follows:

$$C^{FM} = \sum_{d=d_0}^{D} \sum_{t=1}^{T} \sum_{g}^{G} p_{d,t,g}^{FMB} \left[\max\left(f_g\,(q_{d,t,g}) - Q_{d,t,g}^{FM}, 0 \right) \right] \tag{5-14}$$

where the purchasing price $p_{d,t,g}^{FMB}$ is calculated based on the predicted benchmark price $p_{d,t,g}^{FM}$ in FM: $p_{d,t,g}^{FMB} = \beta^{-1} p_{d,t,g}^{FM}$. β is the penalty factor within [0, 1].

5.3.8. Cost of trading in power pool

Power pool features with volatile spot prices and stochastic demand. When the spot price is lower than a certain level, a GENCO is able to fulfill the extra demand by purchasing a part of electricity from the power pool instead of producing by itself. The corresponding purchasing cost can be expressed as the first component in (5-15). At some time intervals, the contract loads cannot be fulfilled because of the physical limits such as ramp up/down rate. A GENCO therefore needs to purchase power from the power pool. The corresponding cost can be expressed as the second component in (5-15). Combing these two components, the cost of trading in power pool C^{PEM} can be expressed as follows:

$$C^{PEM}=\sum_{d=d_0}^{D}\sum_{t=1}^{T}p_{d,t}^{PEM}\left\{\begin{array}{l}I_{d,t}^{EM}\max\left[0,\sum_{i}^{I}\min\left(l_{d,t,i},Q_{d,t,i}\right)-\max\left(G_g^{\min},q_{d,t-1,g}-\Delta G_g^D\right)\right]\\+(1\text{-}I_{d,t}^{EM})\max\left[0,\sum_{i=1}^{I}\min\left(l_{d,t,i},Q_{d,t,i}\right)-\sum_{g=1}^{G}q_{d,t,g}\right]\end{array}\right\} \quad (5\text{-}15)$$

where $I_{d,t}^{EM}$ is an index function, indicating whether a GENCO should buy part of power from the power pool or not.

$$I_{d,t}^{EM}=\begin{cases}1, & p_{d,t}^{PEM}\sum_{g=1}^{G}q_{d,t,g}<\sum_{g=1}^{G}P_{d,t,g}^{FMB}f_g\left(q_{d,t,g}\right)+C_d^{co_2}\\0, & otherwise\end{cases} \quad (5\text{-}16)$$

where the emission cost, $C_d^{co_2}$, is computed according to (5-1).

5.4. Decision Making Model for a GENCO

5.4.1. Formulation of production process

The production process is the first stage of the decision making model, in which a GENCO determines the amount of energy production aiming at maximizing the overall profit from the markets. The optimal output of $\omega_{d,t}$ is solved by DE, along with the $q_{d,t,g}$ dispatched to all its units. For all the units on the current planning day *d**, the production model is expressed as follows:

$$P_{d^*}(\omega_{d,t},q_{d,t,g})=\begin{cases}\max\Gamma_D(\omega_{d,t},q_{d,t,g})\\ s.t.\;\; q_{d,t,g}\le\min\left(G_g^{\max},q_{d,t-1,g}+\Delta G_g^U\right)\\ \qquad q_{d,t,g}\ge\max\left(G_g^{\min},q_{d,t-1,g}-\Delta G_g^D\right)\\ \qquad \sum_{g=1}^{G}G_g^{\max}\ge\sum_{i=1}^{I}\max\left(l_{d,t,i},Q_{d,t,i}\right)+R_{d,t}\end{cases} \quad (5\text{-}17)$$

To account for the physical constraints of each generator, power productions $q_{d,t,g}$ are subjected to the maximum generation outputs $G_g^{\max}$, minimum generation outputs $G_g^{\min}$, and ramp $\Delta G_g^U,\Delta G_g^D$ constraints. Furthermore, spinning reserve $R_{d,t}$ is required to be fulfilled by a GENCO as a whole while all generators are considered available during the whole planning period. Hence the start-up and related costs of the units can be ignored. Based on the solution of the electricity production of all units, the trade-off decisions in EM can be optimized in the first stage of the decision making model.

5.4.2. Formulation of trading process

The second stage of the proposed model is the trading process, in which the trading strategies in FM and CM have to be determined according to the results obtained in the production process. Based on the decision of the energy production, the trading strategy in CM on the current planning day *d** can be solved, along with the trading amount in FM. The trading process (second stage) of the model is expressed as follows:

$$T_{d^*}(c_d^B, c_d^S) = \begin{cases} \max\left\{\Gamma_D(c_d^B, c_d^S) - Penalty_C \times \left[1 - \min\left(C-d, 1\right)\right]\right\} \\ s.t.\ \ (x_D + c_D^B) - (\sum_{t=1}^{24}\sum_{g=1}^{G} e_g(q_{D,t,g}) + c_D^S) \geq 0 \\ \quad c_d^B = \max\left[\sum_{d=d^*}^{D}\sum_{t=1}^{24}\sum_{g=1}^{G} e_g(q_{d,t,g}) - x_d, 0\right] \\ \quad c_d^S = \max\left[x_d - \sum_{d=d^*}^{D}\sum_{t=1}^{24}\sum_{g=1}^{G} e_g(q_{d,t,g}), 0\right] \\ \quad c_d^B \times c_d^S = 0 \end{cases} \tag{5-18}$$

where $x_d = x_{d-1} - \sum_{t=1}^{24}\sum_{g=1}^{G} e_g(q_{d-1,t,g}) + c_{d-1}^B - c_{d-1}^S$ is the stock of a GENCO at the beginning of day *d*. At the beginning of the planning period $d=d_0$, an initial allocated allowance is assumed known from the higher level. The constraints $C_d^B \times C_d^S = 0$ disallow buying and selling allowance simultaneously. The penalty has to be paid on the compliance day *C* if a GENCO cannot match its allowance with the produced emission. The trading volume in CM is solved based on the forecasts of future market prices and emission levels. Generally, the trading profit during the whole planning period is maximized through the volume of allowance traded on day d^*. This is because for periods $[1, d^*-1]$, the decision variables and stochastic parameters of the model are considered fixed at their decided values. Thus, variations in the variables and stochastic parameters are considered only for periods [d^*, D] in the optimization process.

5.4.3. Decision making model

As discussed in Section 5.2.2., a GENCO needs to deicide its stochastic output $\omega_{d,t}$ and arrange all generators' production aiming at maximizing the profit using(5-17). Differential Evolution (DE) is suitable to solve this non-deterministic polynomial-time hard combination optimization problem. After the optimal result of production process is obtained by DE, the decision of allowance trading in CM can be made according to (5-18). The procedures of solving the decision making model are depicted in Fig.5-3.

The model firstly read the input data, including the forecasted spot price of the EM, CM and FM markets, the contract demand, the predicted upper limit of output for the stochastic power pool and the forecasted loading. For each day *d*, there are two continued and interactive process: production process and trading process. After DE initializes the population, mutation and crossover are implemented to generate trial individuals. Each individual represents the value of outputs in each time interval. Economic dispatch (ED) is conducted for all generators in each individual time interval and the corresponding profit is obtained. If the model converges or the maximum iteration number is reached, the optimal decision of the production process is obtained for this time interval. The above mentioned production process computes 24 optimal production decisions and then they are inputted to the trading process. The trading process computes the optimal trading amounts in EM according to (5-7) and (5-15), FM according to (5-10) and (5-14), and CM according to (5-18) for each planning day.

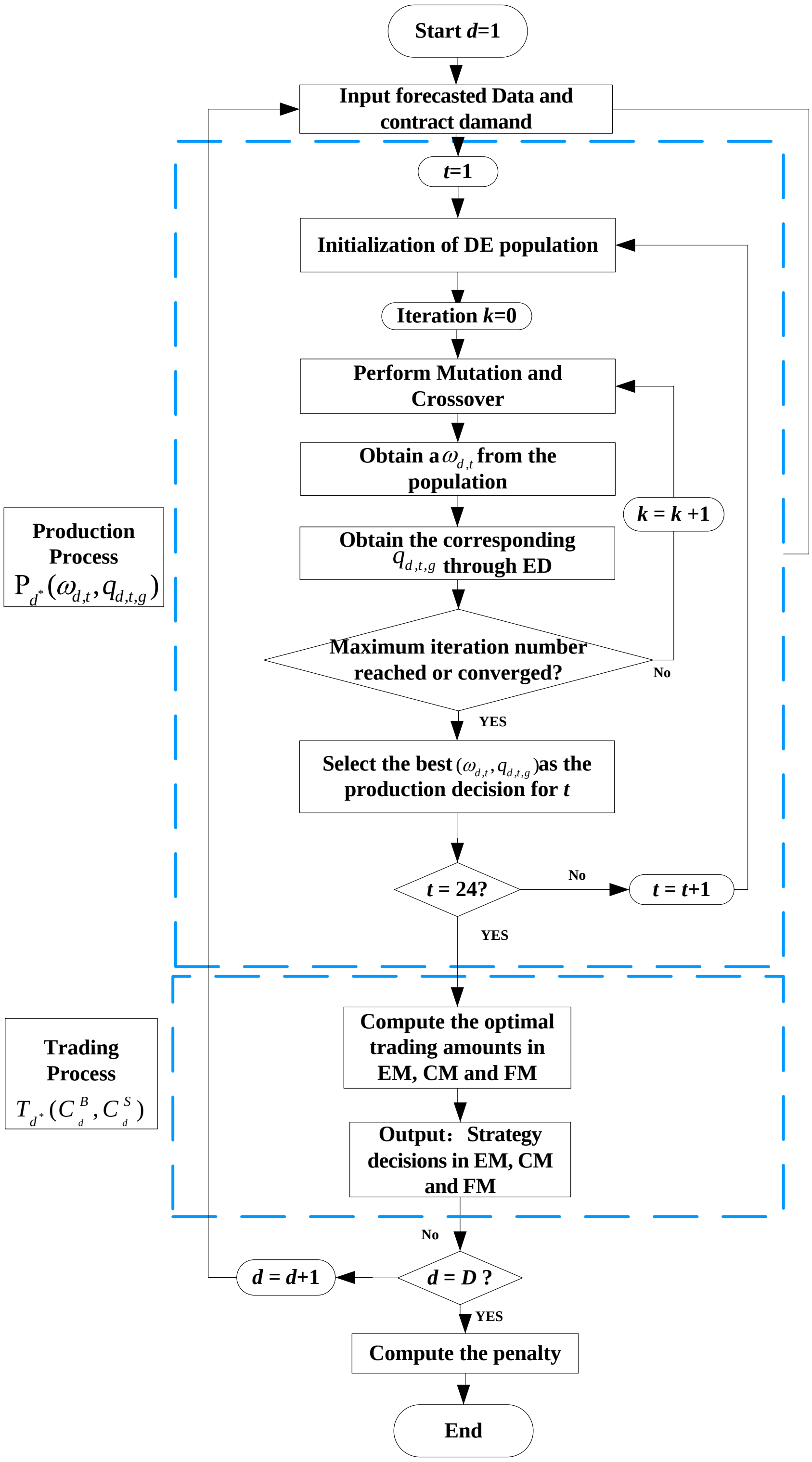

Fig. 5-3 Decision making model of GENCO

5.5. Experiments on The Proposed Model

Table 5-1 Generation limits, fuel parameters and emission factors

	Unit1	*Unit2*	*Unit3*	*Unit4*	*Unit5*	*Unit6*
G_g^{min} **(MW)**	10	20	55	60	100	150
G_g^{max} **(MW)**	100	130	120	180	220	455
a_g **(MMBtu)**	129.97	318.18	126	240	177	480
b_g **(MMBtu/MW)**	32.6	0. 26	8.65	7.74	13.51	7.4
c_g **(MMBtu/MW^2)**	0.0011	0.06	0.0028	0.0032	0.0004	0.0002
Ramp up/down (MW)	50	30	40	75	70	60
Emission factor (kg/MMBtu)	54.01	95.52	74.54	74.54	54.01	95.52
Fuel Type	Gas	Coal	Oil	Oil	Gas	Coal

Table 5-2 Forecasted upper limit of hourly output

Hourly Output (MWh)	**Day 1**	**Day 2**	**Day 3**	**Day 4**	**Day 5**	**Day 6**	**Day 7**
8	700.6	623.7	571.3	603.0	590.0	588.2	605.7
16	720.7	651.5	617.1	628.7	619.6	628.9	652.0
24	552.4	485.4	471.7	453.7	436.7	478.3	484.4

Note: Owing to limited space, only the data of hours 8, 16 and 24 are listed

Table 5-3 Forecasted value of prices in EM

Hourly Price (\$/MWh)	**Day 1**	**Day 2**	**Day 3**	**Day 4**	**Day 5**	**Day 6**	**Day 7**
8	28.6	33.0	37.1	40.1	39.5	42.0	44.0
16	36.8	50.3	58.5	82.5	47.4	38.9	50.6
24	30.3	36.3	36.7	37.5	36.9	36.2	45.1

Note: Owing to limited space, only the data of hours 8, 16 and 24 are listed

The efficient properties of the proposed decision making model are demonstrated through the following experiment. The proposed model is applied to a typical GENCO which owns six thermal generators, including two coal-fired units, two gas-fired units, and two oil-fired units. The details of the generators are provided in Table 5-1. To reveal the impact of different combinations of markets on the decision making of the GENCO, data such as loading, electricity prices, fuel prices are obtained from the Australian Energy Market Operator (AEMO) website [185]. According to [24], the allowance price and penalty price in CM are closely related to the regional/national policy and regulatory issues. The real data of allowance prices in Regional Greenhouse Gas Initiative (RGGI) are used in this study [186]. The real data and forecasted data using the methodology described in chapter 3 are provided in Tables 5-2- Tables 5-5.

Obviously, predictions with high accuracy can benefit the decision making. The time interval for the market clearing is one hour in EM and one day in both CM and FM. For simplicity, it is assumed that all units are available in the whole planning period and the spinning reserve is considered to be 10% of the loading at each time interval. With the help of DE, the proposed model solves a GENCO'S decisions for 7 days by less than 30 minutes, which the computation time are measured on a Dell 2.66GHZ personal computer with 2GB RAM. Therefore, the proposed model is practical for a GENCO to make decision under multimarket environments.

Another major objective of this experiment is to reveal how different market scenarios and their combinations can affect the energy production profile and the trading behavior of the GENCO. It is noticed that the trading behaviors include the trading amounts in the three interactive markets for all the transaction days. Changes including the GENCO's electricity output, related emissions, and daily profits will be compared under different market settings. To achieve these goals, the proposed model solves the decision making problem of maximizing the expected profit subject to the constraints as formulated in (5-17) and (5-18) by 2 continuous processes. For clear illustration purpose, the planning period chosen is only one week. In order to show the influence of different market mechanisms, the whole planning period $d = \{d_0, D\}$ is assumed to be one week before the emission compliance day C (i.e. $d_0 = C - 6,\ D = C$). By the end of the planning period (day D=C), the penalty of excessive emission of the GENCO is computed according to (5-2). Five experiments, described as Scenarios I to V, are carried out to demonstrate the GENCO's optimal decisions under different market environments.

Table 5-4 Forecasted and actual prices in FM

Price ($/MMBtu)	Coal		Oil		Gas	
	actual	forecast	actual	forecast	actual	forecast
Day 1	2.37	2.34	7.21	7.75	4.76	4.64
Day 2	2.39	2.37	7.26	7.20	4.85	4.74
Day 3	2.37	2.39	7.14	7.25	4.74	4.83
Day 4	2.39	2.37	7.21	7.14	4.74	4.72
Day 5	2.35	2.39	7.26	7.21	4.72	4.72
Day 6	2.39	2.35	7.16	7.25	4.65	4.70
Day 7	2.35	2.39	6.93	7.16	4.53	4.64

Table 5-5 Forecasted and actual prices in CM

Price ($/tonne)	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
Actual	4.08	4.02	3.90	3.97	3.97	3.90	3.90
Forecast	4.03	3.90	3.98	3.98	3.90	3.90	3.93

Scenario I (EM with no carbon constraint): The GENCO has only planned for the energy production and trades in EM. It has sufficient initial CO_2 emission allowances so that the market clearing in CM does not affect the GENCO's daily production. Under this scenario, the revenue functions R^{CM} and R^{FM}, cost functions C^{CM} and C^{LFM} are not incorporated in (5-5). In this case, the fuel cost is calculated based on (5-14) while $Q_{d,t,g}^{FM}$ is 0. This is because the GENCO does not own long term contracts for its units. DE would solve the optimum production of electricity without taking (5-1) and (5-2) into account, because no carbon constraint is considered. After the decision of production is made, the model would compute the optimum trading amounts according to and in EM without accounting the other markets.

Scenario II (EM and CM): The GENCO has planned for the energy production and trades in both EM and CM. It has limited initial CO_2 emission allowances so that it has to make a tradeoff between profit-making in both EM and CM, and avoid penalty through the trading in CM. Under this scenario, the revenue function R^{FM} and the cost function C^{LFM} are not incorporated in (5-5). In this case, the fuel cost is calculated based on the forecasted fuel prices because the GENCO does not own long term contracts for its units. DE solves the optimum production of electricity to maximize the profit, and then the decision of trading in both EM and CM can be obtained.

Scenario III (EM with carbon constraint): The GENCO has only planned for the energy production and trades in EM. Initial CO_2 allowances are limited so that it has to make a tradeoff between profit-making and emission penalty. Under this scenario, the revenue functions R^{CM} and R^{FM}, cost functions C^{CM} and C^{LFM} are not incorporated in(5-5). Most of the settings are the same as that in scenario I except the carbon constraints. (5-1) is considered when the GENCO cannot acquire carbon allowances in CM so that it can only tune down its production. Trading in EM is considered and penalty of excessive emission, according to (5-2), is counted in this scenario.

Scenario IV (EM and FM with carbon constraint): The GENCO has planned for both the energy production and trades in EM and FM. It has limited initial CO_2 emission allowances so that it has to make a tradeoff between profit-making and emission penalty. Under this scenario, the revenue function R^{CM} and cost function C^{CM} are not incorporated in (5-5). Most of the settings are the same as that in scenario III, except the consideration of FM. The GENCO owns specified fuel contracts for its six thermal units so that it can make decisions on how to use the amount of fuel basing on the solution of the proposed model. Besides the decision of electricity production, the model also provides trading decisions in both EM and FM.

Scenario V (EM, CM and FM): The GENCO has planned for the energy production and trades in EM, CM and FM. It has limited initial CO_2 emission allowances so that it has to make a tradeoff among all markets, and avoid penalty through the trading in CM. In this case, all the market factors are taken into account and the GENCO has more options to make a tradeoff between making profit through power production and emission reduction.

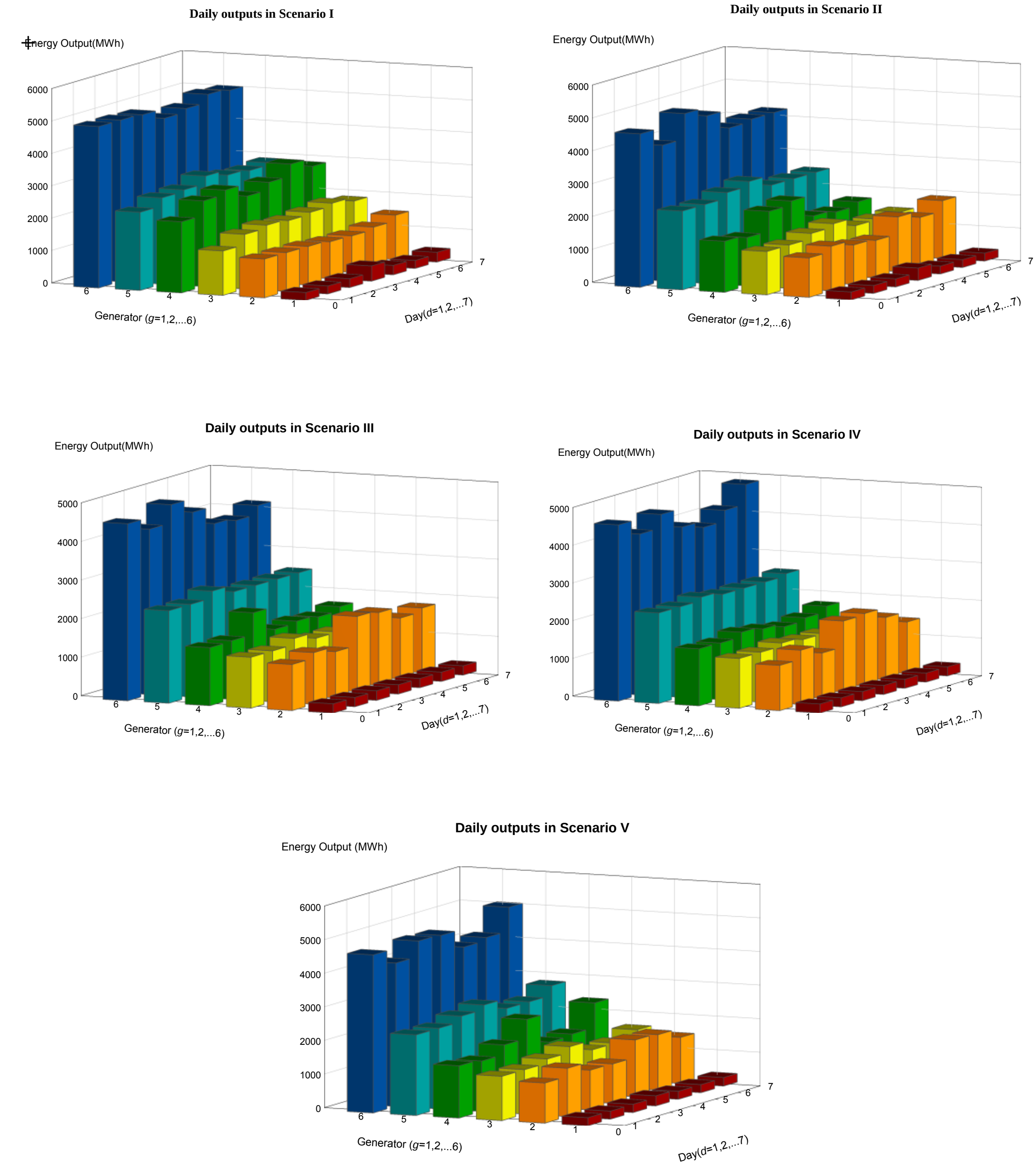

Fig. 5-4 Daily energy outputs in scenarios I to V

Fig.5-4 shows the daily energy outputs of the six units for the five scenarios. Unit 1 is a gas unit which is scheduled least in all the scenarios as it has a higher fuel consumption function. On the contrary, unit 6 is a coal unit which provides a high percentage of energy although it has the highest emission factor. Unit 2 usually generates more than 1500 MWh daily while unit 6 usually generates less than 5000MWh daily. The two main reasons that the unit 2 have higher priority (>48%) than unit 6 (<45%) are: 1) the maximum output $G_g^{\max}$ (MW) of unit 2 and unit 6 is 100MW and 455MW, respectively; 2) The difference in ramp up/ down constraints. In comparison with the others, oil units 3 and 4 are affected more significantly by different scenario settings. It is due to the fact that they are the marginal units in the production process. The total production in scenario I is 94,064 MWh and about 80,000 MWh in both scenarios III and IV.

It is obvious that the GENCO would produce as much as it can in scenario I to maximize its profit in the EM. The main reason of not taking the emission amount into account is that the GENCO has been allocated sufficient allowances. In scenario II the GENCO produces 81094.7MWh which is slightly more than that in scenarios III and IV. This is because the GENCO also seeks for profit in CM or FM in some time intervals. Furthermore, due to the incorporation of the three interactive markets, the GENCO can take advantage of the trades in FM and CM to increase its production using the proposed decision making model. It produces more (83008MWh) in scenario V than that in scenarios II, III and IV.

Although the units are not scheduled freely due to the emission constraints, the proposed model can make a good tradeoff between profit-making and emission reduction under the three interactive markets environment. On the whole, different carbon reduction policies affect the GENCO's daily production. From the view of EM operation, the reduction of the GENCO's production would lead to increases in EM prices in the short term. On the other hand, the GENCO might consider investing in renewable units according to the price variations in CM and FM.

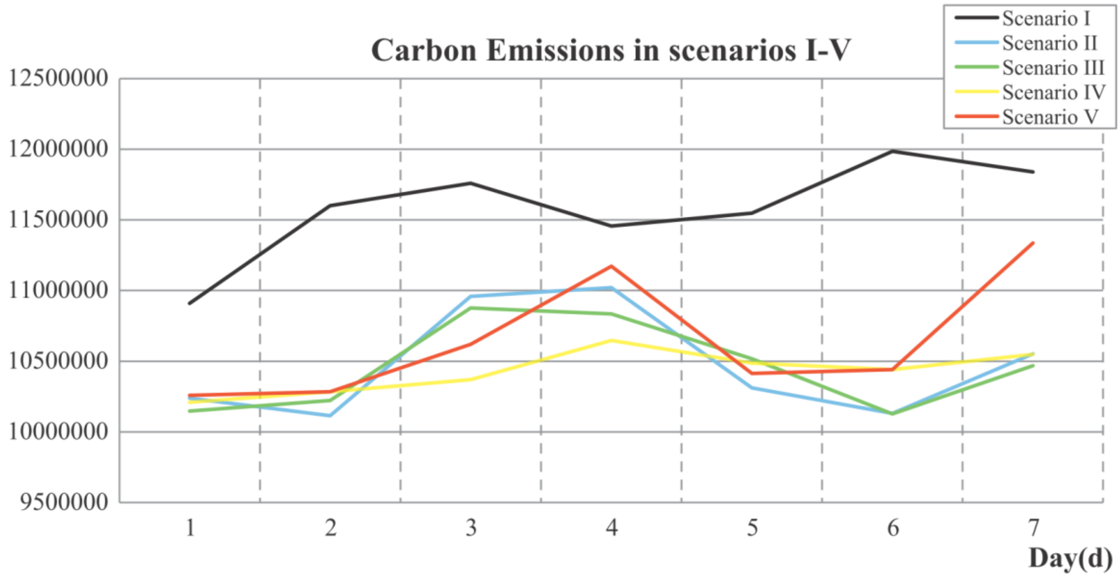

Fig. 5-5 Daily emissions in scenarios I toV

Fig.5-5 shows the daily emission in different scenarios. It can be seen that, as emission constraint has not been taken into account, the emission produced in scenario I is the highest. Due to insufficient emission allowances, the emission levels in the other scenarios are relatively low throughout the planning period. The fourth scenario yields the lowest emission because the GENCO cannot acquire extra allowances so that it needs to reduce the output of its less efficient units to seek for profit from FM. Furthermore, the GENCO's emission level in scenario V is the second highest as a good tradeoff decision, committing the emission constraint, has been made. Under the carbon market environment, the GENCO's emission is directly related to some fundamentals such as carbon prices, amount of emission allowances, emission cap and penalty price. A strict constraint of course would lead to a lower level of carbon emission. The carbon market mechanism might bring about a moderate level of emission.

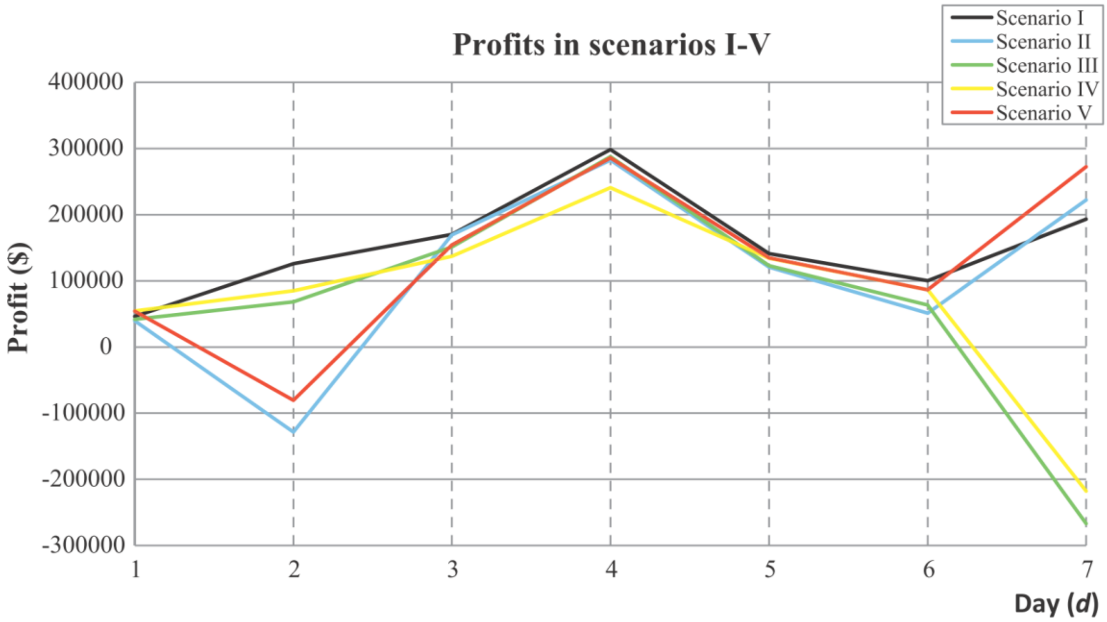

Fig. 5-6 Daily profits in scenarios I to V

Fig.5-6 shows the daily profits in the five scenarios. It can be seen that the profits in scenarios I, III and IV are similar, with the exception on the last (7^{th}) trading day. This is the emission compliance day on which, except in scenario I, the GENCO needs to settle the emission penalty. It can be observed that the profits in scenarios III and IV decrease while the profits in scenarios I, II and V increase on day 7. This is because scenario I does not include emission constraint while scenarios II and V have carbon market trading. Furthermore, the GENCO earns slightly more in scenario IV than that in scenario III during the whole planning period because it can seek for profit in FM in addition to EM. Due to the same reason, the GENCO's profit obtained in scenario V is higher than that in scenario II. Excluding the compliance day, the shape of the profit profiles in scenarios II and V are different from the others. The GENCO decides to purchase emission allowances in day 2 and sell them in days 3 and 4 to make profit from CM in addition to EM and FM. On the whole, the implementation of environmental policy would lead to a reduction of GENCO's profit. However, the decrease can be alleviated through the trading in the other markets under the multimarket environment. It can be observed from figures 5-5 and 5-6 that the GENCO's tradeoff decision between profit-making and emission reduction are significantly different in various scenarios. Consistent with the extent of the European ETS, in this study, it is supposed that this market is very large and GENCOs are price takers. Therefore, the carbon allowance price is given exogenously. GENCOs have to purchase allowances whenever the initial allocation is insufficient to cover their actual emissions.

Table 5-6 Summaries of the five scenarios

	Scenario I	Scenario II	Scenario III	Scenario IV	Scenario V
Energy Production(MWh)	94,064	81,095	80,015	80,082	83,008
Carbon emission (tonne)	81,095	73,327	73,196	72,988	74,527
Profit in EM($)	4,053,545	3,291,844	3,436,742	3,594,896	3,821,409
Profit in FM($)	NA	NA	NA	320,739	123,828
Profit in CM($)	NA	-56,396	NA	NA	-91,016
Total profit($)	1,075,757	756,777	469,179	520,238	907,309

A summary of the performances of the five scenarios and the impacts of ETS on the GENCO is provided in Table 5-6. Besides the profits and emission in the planning period, it can be conjectured that ETS would adjust the GENCO's portfolios of planning at the high levels in the hierarchical decision making model. The implementation of carbon policies would immediately lead to a drop of the GENCO's profits. However, the GENCO could accommodate itself to make a good tradeoff between profit-making and emission reduction under the multimarket environment. For the real practice in the long run, the impacts of CM are expected to be larger so that the trades in EM and CM can influence each other. Although this study includes the FM externalities, embodied in fuel price variations, it does not take fuel portfolio building into account. It is an essential problem for a GENCO as it has to account for potential fuel contracts characteristics, transportation contracts, storage/consumption commodity and other services, which can be included in our further studies. It can also be conjectured that the impact of FM on the profit of GENCO would be larger when the above mentioned factors are taken into account.

5.6. Summary

Chapter 5 covers electricity market, carbon market, and fuel market and contributes for a comprehensive short term electricity market planning model. In this chapter, a novel decision making model under multi-market environment is developed based on the studies in previous chapters. This model investigates the impacts of carbon policies with interactive markets on the decision making of a GENCO. It has two sequential processes. The first one is the production process which is solved by DE and the second one is the trading process involving three interactive markets.

The proposed model in this chapter accounts for emissions trading mechanisms by incorporating emissions constraints as well as the trading of emission allowances. Thus, this model allows for analysis of how different market mechanisms affect a GENCO's behavior and its overall profits. A comparative experiment is carried out to reveal a GENCO's operation subject to different policy scenarios.

A. From EM's point of view, a GENCO would reduce its production so that prices in EM are expected to be increased in the short term. Furthermore, a GENCO would consider investing in some renewable units with merit priority in production planning.

B. From CM's viewpoint, a harsh cap of emission would lead to a significant bring down of carbon in a short period while GENCOs are expected to pass the cost to their customers. On the other hand, CM might bring about a moderate level of emission and the market mechanisms are expected to reveal the true value of carbon allowances.

C. From the standpoint of FM, transaction of fuel is a good supplement for GENCOs to operate in EM and CM.

D. In summary, the proposed model lets GENCOs to make a good tradeoff between profit-making and emission reduction under three interactive markets environment. Furthermore, policies defining the three interactive markets may lead to a better environment for electricity industry to achieve the intended goals such as emission reduction, promoting renewable, and keeping electricity cost at a reasonable level.

CHAPTER 6. IMPACTS OF EMISSION TRADING AND RENEWABLE ENERGY SUPPORT SCHEMES ON ELECTRICITY MARKET OPERATION

6.1. Introduction

Chapter 5 proposed a novel dynamic decision making model to deal with the multimarket trading problem for a GENCO during each trading period. It covers electricity market, carbon market, and fuel market and contributes for a comprehensive short term electricity market planning model. Renewable market is the next focus according to the research route depicted in Figure 1-1. As described in Section 2.4.3, renewable energy support scheme (RESS) and emission trading scheme (ETS) have overlapping goals with respect to the global environmental and economical benefits. Inevitably, the implementation of these two schemes would bring some new problems to electricity market operation. Given this background, chapter 6 endeavors to covers electricity market, carbon market, and renewable market and examine the impacts of the two schemes on the electricity market operation. With the implementation of these two schemes, an agent-based market simulation method is proposed in this chapter for analyzing the gaming behaviors of generation companies in an open electricity market environment.

ETS has been comprehensively introduced in Section 2.3.1. Cap and trade program, which is the most widely adopted method of carbon market (CM), is the focus of this thesis. When ETS is implemented, a GENCO should possess corresponding emission allowances when it emits CO_2. If the emission allowances are not freely allocated, a generation company would need to pay for them. A coal-fired plant emits more than twice the amount of CO_2 than a gas-fired or combined cycle gas turbine (CCGT) plant for generating one unit of electrical energy. Thus, under ETS, the production cost of a coal-fired plant would increase much more than that of a gas-fired or CCGT plant. As a result, a coal-fired plant would lose its dominance due to the relatively higher production cost and its output has to be decreased. On the other hand, the difference in production costs between a gas-fired or CCGT plant and a coal-fired plant would be reduced and the outputs of the gas-fired or CCGT plant would be increased. In this way, the emission reduction target might be reached.

RESS has been investigated in Section 2.3.4. Its objective is to promote the rapid development of the renewable energy sources. In many countries, different incentive policies have been established in renewable market (RM). The feed-in tariffs mechanism, one of most important methods under fixed price systems, is the focus of this chapter. Under RESS, the development of renewable energy sources are usually supported or inspired by governments and generally can get priority and subsidy to generate electricity. This may reduce the demand for traditional thermal generation electricity technologies and further reduce the CO_2 emissions.

Section 6.2 proposed the agent-based market simulation method, followed by the introduction of a methodology to simulate the operation process of a specified electricity market in Section 6.3. The proposed model can be used to analyze the gaming behaviors of generation companies in an electricity market environment with the participant in CM and RM. Section 6.4 then presents some indices employed to evaluate the market operation states. A comprehensive experiment demonstrates the feasibility of the developed model and methodology is provided in Section 6.5. Section 6.6 summarizes this chapter with concluding remarks.

6.2. Agent-Based Simulation Model in the Electricity Bidding Market

During the past two decades, agent-based computational economics (ACE) has been gradually developed. In ACE, the market participants are represented by agents with self-adaptive and self-learning abilities. Agents would keep adjusting their strategic behaviors in the process of market competition for profit maximizing according to varying market information. Simulation model is usually set up according to market rules. During the progress of the simulation steps, the system would gradually evolve into a steady state. The market characteristics can then be studied based on the steady market state.

The concept of agent-based simulation seeks to overcome some of the weaknesses of conventional modeling approaches by building a simulation from a player's perspective which helps to integrate aspects such as player strategies, learning effects, or imperfect markets and information. The approach of agent-based simulation relates to concepts of several disciplines such as economics, game theory and software engineering [187, 188].

If the electricity auctions were held only once, characterizing the market clearing price as Nash equilibrium would be rather simple. Since the electricity auctions are held repeatedly, however, there is a myriad of Nash equilibrium in this game. In order to deal with the complexity of repeated games, agent-based simulation would be a suitable method. Electricity auctions in England and Wales [189-191] have been analyzed using agent-based simulation in order to investigate the markets from the aspects of market clearing price, collusion, and exercising of market power.

Many algorithms have been applied in the agent-based simulation model. The Roth/Erev algorithm [192] is one kind of reinforcement learning algorithm and is the earliest one used in the agent-based market simulation model. It includes three learning parameters namely initial propensity parameter, forgetting parameter and experimentation parameter. The calculation experience has shown that, in order to gain better learning efficiencies and convergences, it is necessary to set the three parameters properly [192]. However, this work is usually rather difficult.

In this chapter, replicator dynamics algorithm [193], which belongs to evolution game theory and can reasonably describe the change trend of population behavior and predict the individual behavior, is employed to simulate the bidding strategies of generation companies. Replicator dynamics algorithm uses very few parameters and its steady state is also a Nash equilibrium point [193-195]. This algorithm is introduced in the following sub-section 6.2.1.

6.2.1. Replicator dynamics algorithm

Considering a non-cooperation game process with N agents, each agent j has a strategy set A_j. Assume A_j involves K discrete strategies and the probability for agent j to choose the k^{th} strategy is Pr_{jk}. According to the probability Pr_{jk}, agent j would choose the k^{th} strategy from its strategy set A_j based on roulette wheel selection. If all agents have chosen their strategies, a game situation would be formed.

Each agent j can get a particular profit π_j from a given game situation, and thus a mapping from the game situations to the profit of each agent can be obtained. Here the so called learning is that agent j would modify its probability to choose the corresponding strategy in the next round according to its profit in the current round. The difference between the current profit and the average profit can be adopted as the learning drive or stimulation. Here the average profit is the average value of the profit of the previous N_T training rounds before the current round. The learning utility U_j of agent *j* can be defined as:

$$U_j = \pi_j - \overline{\pi_j} \tag{6-1}$$

$$\overline{\pi_j} = \sum_{l=N_{run}-N_T}^{N_{run}-1} \pi_j(l) \Big/ N_T \tag{6-2}$$

where π_j represents the profit of agent *j* in the current round; $\overline{\pi_j}$ represents the average profit of agent *j*; $\pi_j(l)$ is the profit of agent *j* in the l^{th} round; N_{run} is the current round number.

Note that this algorithm does not directly use the profit to conduct the learning. Instead, the difference between the current profit and the average profit of the previous N_T rounds is used as the learning drive. If the difference is less than zero, it means that the current strategy is not a good one and the probability to choose this strategy would be decreased. Notice that the average profit $\overline{\pi_j}$ would keep changing as the iteration process is progressing. Hence, using $\overline{\pi_j}$ as the criterion, the stimulation effect of the past events can be gradually weakened.

Assuming agent *j* has chosen strategy *h* in the l^{th} round and obtains the learning utility $U_{jh}(l)$, the new probability to choose strategy *k* in the next round can be calculated as follows:

$$S_j(l) = \delta \cdot \left| U_{jh}(l) \right| \tag{6-3}$$

$$q_{jk}(l) = \mathrm{Pr}_{jk}(l) \cdot S_j(l) \tag{6-4}$$

$$E_{jk}(l) = \begin{cases} U_{jh}(l), & k = h \\ 0, & k \neq h \end{cases} \tag{6-5}$$

$$q'_{jk}(l) = q_{jk}(l) + E_{jk}(l) \tag{6-6}$$

$$\mathrm{Pr}_{jk}(l+1) = q'_{jk}(l) / \sum_k q'_{jk}(l) \tag{6-7}$$

where $S_j(l)$ represents the total trend of agent j after standardization processing in the l^{th} round; δ represents the standardization coefficient; $q_{jk}(l)$ represents the trend of agent j to choose strategy k after standardization processing in the l^{th} round; $\Pr_{jk}(l)$ represents the probability to choose strategy k in the l^{th} round; $E_{jk}(l)$ represents the adjusted amount of the trend of the agent j to choose strategy k; $q'_{jk}(l)$ is the adjusted trend of the agent j for strategy k after the l^{th} round; $\Pr_{jk}(l+1)$ represents the renewed probability for the agent j to choose strategy k in the $(l+1)^{\text{th}}$ round .

This learning algorithm has avoided the coordination problem of too many learning parameters existing in the Roth/Erev algorithm [192]. In this algorithm, only one parameter δ needs to be set. If the value of δ is too big, the learning speed would be slow. On the other hand, if the value of δ is too small, $E_{jk}(l)$ would take a big proportion in (6-6), which may result in too big change of the probability and convergence problem. Calculation experience has shown that when δ is set to 20~100, the algorithm would have good convergence [193].

6.2.2. The bidding strategies of GENCOs considering emission costs

Assuming, under ETS, GENCO(Agent) j needs to purchase CO_2 emission allowances from a carbon market with price p_{co2}, its production cost and marginal cost can be represented as follows:

$$C_j(P_{t,j}) = (b_j + p_{co2}\eta_j)P_{t,j} + 0.5c_j P_{t,j}^2 \tag{6-8}$$

$$M_j(P_{t,j}) = (b_j + p_{co2}\eta_j) + c_j P_{t,j} \tag{6-9}$$

where $C_j(P_{t,j})$ is the production cost of GENCO j including CO_2 emission cost; b_j and c_j are the production cost constant coefficients of GENCO j which can be obtained from historical data; $P_{t,j}$ is the output of GENCO j at hour t; η_j is the CO_2 emission factor of

GENCO j; $M_j(P_{t,j})$ is the marginal cost of GENCO j. In order to compare the GENCOs' performances under different scenarios, the term $p_{co2}\eta_j$ is added before $P_{t,j}$ in Eq. (6-8). As a result, Eq. (6-9), the marginal cost function, has two independent terms $p_{co2}\eta_j$ and $P_{t,j}$ and hence scenarios with or without carbon market can be simulated.

Suppose that there are n independent GENCOs (agents) participating in a pool-based single-buyer electricity market in which sealed auction with a uniform market clearing price (MCP) is employed. Using equations (6-12) - (6-14), the market clearing price can be obtained through the market clearing process described in section 6.3. The linear supply function can be found in equation (6-12). Here it is assumed that each GENCO is required to submit a linear supply function to the pool together with the generation output limits for each of the 24 hours in the day-ahead market [196] and GENCO j has a strategy set with K strategies and each strategy is formed by fixing the constant part of the marginal cost $M_j(P_{t,j})$ and multiplying the first order part of the marginal cost with a coefficient D ($D \in [D_{\min}, D_{\max}]$). The range of D would be divided into K equal parts, where $D_{\min}$ and $D_{\max}$ are the lower limit and upper limit of the range, respectively. Thus, if an agent j has chosen the i^{th} strategy, the corresponding coefficient is:

$$D_i = D_{\min} + \frac{i}{K-1}(D_{\max} - D_{\min}) \tag{6-10}$$

Thus, the bidding price of agent j can be represented as:

$$B_j(P_{t,j}) = b_j + p_{co2}\eta_j + D_i c_j P_{t,j} \tag{6-11}$$

6.3. Operation Indices of the Electricity Market

It is assumed that RESS adopts the feed-in tariffs mechanism. In this case, all renewable energy would be purchased at a guaranteed premium price $p_{renewable}$ in the renewable market. The market clearing process of non-renewable energy in the electricity market at hour *t* can be described as:

$$b_j + p_{co2}\eta_j + D_i c_j P_{t,j} = R_t \quad j = 1,2,...,n\,; \quad t = 1,2,...,T \tag{6-12}$$

$$\sum_{j=1}^{n} P_{t,j} = L_t - P_{renewable,t} \quad t = 1,2,...,T \tag{6-13}$$

$$x_{t,j} P_{j\min} \le P_{t,j} \le x_{t,j} P_{j\max} \quad j = 1,2,...,n\,; \quad t = 1,2,...,T \tag{6-14}$$

where R_t is the market clearing price at hour *t*; *n* is the number of the agents in the market; T is the number of the hours over the studied time horizon; L_t is the forecasted load at hour *t*; $P_{renewable,t}$ is the forecasted renewable energy at hour *t*; $x_{t,l}$ represents the operation state of GENCO *j* at hour *t* (1: operation; 0: down); $P_{j\max}$ and $P_{j\min}$ are the upper and lower output limits of GENCO *j*. Notice that, in the electricity market in which sealed auction with a uniform market clearing price is employed, the left hand side of (6-12) is a linear supply function of GENCO *j* at time *t* and (6-12) is used to determine the output of GENCO *j* at time *t*.

The following operation indices of the electricity market can be defined:

A. Average market clearing price $\overline{R}$ over the studied time horizon *T*

$$\overline{R} = \frac{\sum_{t=1}^{T}\sum_{j=1}^{n}(P_{t,j}R_t)}{\sum_{t=1}^{T}\sum_{j=1}^{n}P_{t,j}} \tag{6-15}$$

B. Average electricity purchasing price $\overline{p_{elect}}$ over the studied time horizon *T*

$$\overline{p_{elect}} = \frac{\sum_{t=1}^{T}\sum_{j=1}^{n}(P_{t,j}R_t) + \sum_{t=1}^{T}(P_{renewable,t}\,p_{renewable})}{\sum_{t=1}^{T}L_t} \tag{6-16}$$

C. Total CO_2 emission amount E_{total} over the studied time horizon *T*

$$E_{total} = \sum_{t=1}^{T}\sum_{j=1}^{n} P_{t,\,j}\eta_j \tag{6-17}$$

D. Market share θ_j of agent *j* over the studied time horizon *T*

$$\theta_j = \frac{\sum_{t=1}^{T} P_{t,\,j}}{\sum_{t=1}^{T}\sum_{j=1}^{n} P_{t,\,j}} \tag{6-18}$$

E. Capacity factor CF_j of agent *j* over the studied time horizon *T*

$$CF_j = \frac{\sum_{t=1}^{T} P_{t,\,j}}{TP_{j\,\max}} \tag{6-19}$$

6.4. Market Simulation Process

Using the learning algorithm described in Section 6.2.1, the whole operation process of the electricity market over the studied time horizon can be simulated. The concrete steps are listed as follows:

A. Set time counter t=1.

B. Obtain the predicted system load L_t and the output of renewable energy resources, $P_{renewable,\,t}$.

C. Set l=0.

D. Set $l=l+1$, generate randomly the bidding data of the agents.

E. Using (6-12)-(6-14), solve the market bidding model. The market clearing price, the outputs and the corresponding profits of the agents can be obtained.

F. Repeat steps *D.* and *F.* for N_T times where N_T is the number of training rounds for market simulation.

G. The training for market simulation ends and the agents start learning. Set k=0 and the same initial probability for each agent to choose any bidding strategy.

H. Set k=k +1 , l=N_T+ k , generate randomly the bidding data of the l^{th} round in a roulette manner.

I. Using (6-12)-(6-14), solve the market bidding model. The outputs and the corresponding profits of the agents in the l^{th} round can be obtained.

J. According to the profit of the l^{th} round and the average profit of the former N_T training rounds, use (6-1)- (6-7) to calculate the probability of the $(l+1)^{th}$ round to choose each strategy.

K. Examine if the simulation process is convergent. The criterion is that if the probabilities of the bidding strategies of all agents have exceeded a specified threshold, the simulation process is considered to be convergent in a steady state. If the simulation process is convergent, go to step *L.*；Otherwise return to step *H*.

L. Calculate the market clearing price, the outputs and the corresponding profits of the agents in the steady state.

M. If $t \geq T$, go to step *N.*； Otherwise, set t=t+1 and return to step *B*.

N. Using (6-15)-(6-19), calculate the operation indices of the electricity market.

6.5. Experiment on The Agent-based Simulation Model

Suppose that there are four GENCOs participating in the operation of an electricity market. In order to simplify the situation, each GENCO is assumed to possess one generation unit. The generation units of the first three GENCOs are all coal-fired, while the generation unit of the fourth GENCO is a CCGT. The production cost function coefficients, output limits as well as the CO_2 emission factors of these four GENCOs are listed in Table 6-1. The techno-economic data of Table 6-1 are obtained from [196-198] with some modifications. It should be emphasized here that the proposed methodological framework in this chapter is applicable to general cases.

Table 6-1 Techno-economic parameters for the generation units of the four GENCOs

No.	b_j (\$/MWh)	c_j (\$/MW^2 h)	$P_{j\ min}$ (MW)	$P_{j\ max}$ (MW)	η_j
1	13.64	0.121	30	160	0.918
2	12.28	0.081	40	200	0.958
3	11.52	0.086	40	200	1.125
4	20.80	0.150	0	160	0.426

Assuming that the studied time horizon is 52 weeks and the predicted system load L_t are listed in Table 6-2. Besides, for reducing the calculation time, the average load of each week is used to represent the characteristics of the weekly load. The major objective of this chapter is to study the interaction among EM, CM, and RM. The combination of ETS and RESS can affect the operation of the electricity market significantly.

Table 6-2 The predicted weekly system average loads (MW)

Week	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
Load	530	510	515	500	495	480	500	510	510	520	520	520	530
Week	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
Load	520	520	550	550	550	560	560	570	570	575	575	580	580
Week	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
Load	580	600	600	600	610	610	610	640	640	630	630	615	615
Week	**40**	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
Load	600	590	590	580	570	570	565	560	555	550	550	545	540

Table 6-3 The predicted weekly average outputs from renewable energy (MW)

Week	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
Output of Renewable energy	60	50	65	60	55	50	45	40	40	50	50	50	**60**
Week	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
Output of Renewable energy	65	70	70	75	60	60	65	65	75	75	80	80	80
Week	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
Output of Renewable energy	90	90	100	100	80	80	70	65	65	75	75	80	80
Week	**40**	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
Output of Renewable energy	80	75	75	80	80	80	90	90	80	75	70	65	65

The four experiments, described as Scenarios I to IV, are carried out:

Scenario I: Both ETS and RESS are not implemented in the market and there is also no renewable energy in the market (Only EM).

Scenario II: Only RESS is implemented in the market and the system operator needs to purchase all renewable energy (here assuming the renewable energy is wind energy). The fixed purchase price is 70 $/ MWh and the predicted outputs of the renewable energy sources are listed in Table 6-3 (Only RM and EM).

Scenario III: Only ETS is implemented in the market and each Genco must purchase an equivalent number of allowances from emission allowances trading market for emitting a specific amount of CO_2. The price of CO_2 allowances is fixed at 20$/ton (Only CM and EM).

Scenario IV: Both ETS and RESS are implemented in the market and the designs of the two schemes are the same as that in scenario II and scenario III (RM, CM, and EM).

Set δ =50, N_T=500, K=5, D_{min}=1, D_{max}=2 and the threshold to examine if the simulation process is convergent to be 0.95. The criteria used to set the parameters δ, NT and the threshold relating to the replicator dynamics algorithm can be found in reference [193]. The criteria used to set the parameters K, D_{min} and D_{max} relating to the bidding strategies can be found in reference [196]. Using the procedures outlined in Section 6.4, the market operation indices in scenarios I-IV can be calculated and the results are listed in Table 6-4. The calculated capacity factors are shown in Fig.6-1.

Table 6-4 Operation indices of the electricity market under different scenarios

Scenario	$\overline{R}$ **(\$/MWh)**	$\overline{p_{elect}}$ **(\$/MWh)**	E_{total} **(million ton)**	**Market share of Genco 4 ,** θ_4
1	30.70	30.70	46.05	11.79%
2	27.54	32.85	41.22	9.18%
3	48.54	48.54	41.84	22.88%
4	46.46	49.40	36.42	23.32%

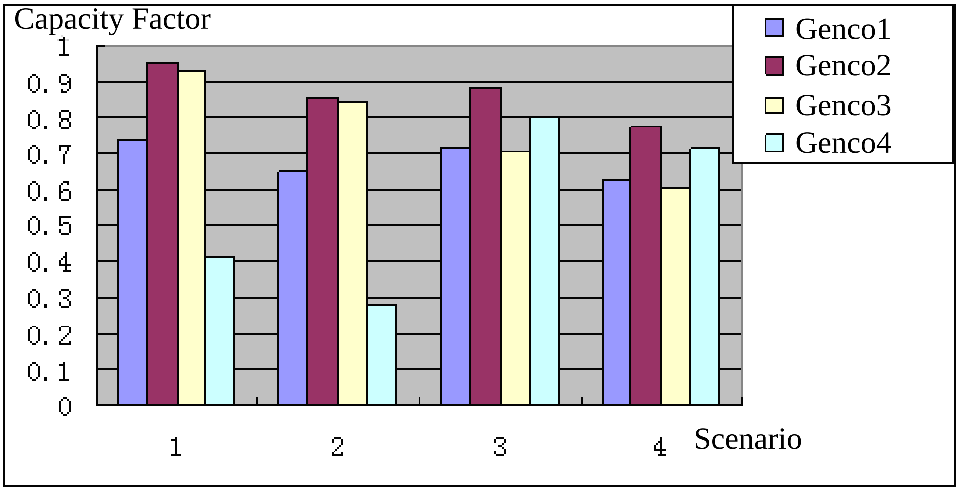

Fig. 6-1 Capacity factors of generation companies in different scenarios

It can be observed from Table 6-4 and Fig. 6-1 that in scenario II, due to the reduction for the need of the thermal electricity generation, the market clearing price $\overline{R}$

has decreased 3.16$/ MWh compared with that in scenario I. However, because the system operator needs to purchase renewable energy in a rather high price (70 $/MWh), its average purchasing electricity cost has increased 2.15 $/MWh compared with that in scenario I. According to RESS subsidize from the government should be made. Here, the subsidy cost would be 5.31$/MWh. Moreover, compared with scenario I, Gencos can reduce CO_2 emissions 4.83 million ton but on the other hand, the market share of Genco 4 has decreased to the least among the four scenarios. As shown in Fig.6-1, the capacity factor of Genco 4 in scenario 2 is only 0.281.

In scenario III, the implementation of ETS has resulted in a rather big rise of the market clearing price $\overline{R}$ (from 30.7$/MWh to 48.54$/MWh), the rise magnitude has accounted for 89.2% of the CO_2 emissions price. In addition, the total CO_2 emission amount has decreased to 41.84 million ton and, comparing with scenario I, 9.14% emissions amount is reduced. Besides, the market share of the CCGT unit (Genco 4) has been significantly improved, from 11.79% to 22.88% and the rise is 95%. The capacity factor of Genco 4 is also the highest among the four scenarios as shown in Fig.6-1.

In scenario IV, when both RESS and ETS are implemented, the market clearing price $\overline{R}$ has decreased 2.08 $/MWh and the electricity purchasing cost has increased 0.86 $/MWh compared with scenario III. Compared with scenario II, the subsidy has decreased to 2.94 $/MWh. In addition, the total CO_2 emissions amount has decreased to 36.42 million ton and the decrease is 21% compared with scenario I. The total reduced emissions amount has exceeded the summation of that in scenarios II and III. Besides, the indices of market share and capacity factor have shown that Genco IV possesses a rather large market share and a rather high capacity factor.

Based on the above findings, the impacts of ETS and RESS on electricity market operation can be summarized as:

A. When only ETS is implemented, both the market clearing price and the electricity purchasing price would rise. In addition, Gencos with low CO_2 emission can obtain larger market shares, which is advantageous to achieve the CO_2 emission reduction target. However, under this condition, renewable energy sources cannot be incited to develop rapidly and in the long run, would make the CO_2 emission reduction unsustainable.

B. When only RESS is implemented, the government needs to bear a rather high subsidy to the system. In addition, though CO_2 emission amount can be reduced to some extent in the short run, this mechanism may result Gencos with low emission factors possess very small market share. In the long run, these Gencos with low emission factors would have to retreat from the market. Contrarily, Gencos with high emission factors can get larger market shares. This may weaken the effect of CO_2 emission reduction from the renewable energy sources and is disadvantageous to the optimization of energy source structure.

C. When both ETS and RESS are implemented, the subsidies provided by the government would decrease considerably compared with the condition when only RESS is implemented. In addition, CO_2 emission amounts would also be decreased considerably and Gencos with low emission factors would possess a rather large market share. Thus, on one hand, RESS can promote rapid development of renewable energy sources and reduce the demand of the traditional thermal electricity generation technologies. This is advantageous to the reduction of the CO_2 emissions. On the other hand, Gencos with low emission factors possess large marker shares, which may incite generation investors to invest the generation technologies with low CO_2 emission such as CCGT and the energy sources structure can be further optimized.

6.6. Summary

The major objective of this chapter is to study the interaction among EM, CM, and RM. The combination of ETS and RESS can affect the operation of the electricity market significantly. In order to investigate the impacts of emission trading and renewable energy support schemes on electricity market operation, replicator dynamics algorithm is employed in this chapter to study the bidding strategies of generation companies. Section 6.2 proposes an agent-based methodology to simulate the operation process of the electricity market. Some indices are employed to examine the market operation performance in Section 6.3 and used to analyze the impact of ETS and RESS on the electricity market. The modeling and analysis of different scenarios in Section 6.4 have shown that only when both ETS and RESS are implemented, CO_2 emission reduction can be sustainable and the energy sources structure in the future can be optimized.

CHAPTER 7. MULTIMARKET ANALYSIS OF GENCO'S OPERATIONS CONSIDERING EMISSION TRADING AND RENEWABLE ENERGY SUPPORT SCHEMES

7.1. Introduction

As discussed in Section 1.3, this thesis aims at developing novel frameworks for electricity market planning and management under multimarket environment. The market prospect and a GENCO's attitude toward climate change will finally determine its long term planning. In the short term, developing an efficient planning model for GENCOs to handle uncertainties in the interactive markets is a challenge and significant task. Chapter 5 proposes a novel dynamic decision making model which covers GENCO's planning in EM, FM, and CM. Chapter 6 attempts to study the interaction among EM, CM and RM from the aspect of electricity market operation. Based on the finding from previous chapters, chapter 7 is dedicated to propose the planning model from the GENCO's aspect, which under a multimarket environment consists of EM, CM, FM, and RM. Similar to chapter 5, it will be based on a two stage framework which can embody the trading behavior of a GENCO under multimarket environment. Similar to chapter 6, the impact of ETS and RESS on electricity market is investigated in this chapter. However, several features distinguish this chapter with the previous ones.

Chapter 7 identifies the role of wind power under both ETS and RESS. It has great contributions to the electricity market planning and operation. The increasing environmental challenges force enterprises to modify their system operation routines to reduce carbon emissions. As discussed in Section 2.4.4, exploiting renewable energy is an effective way to mitigate energy source deficiency, control GHGs emissions, and achieve smart grid vision [199, 200]. Wind power being one of the most appealing renewable energy resources has gained widespread concerns during the last decades. Along with the introduction of various emission reduction schemes, increasing number of wind turbines have been installed around the world [201]. However, due to the intermittent and stochastic characteristics of wind resource, wind power brings great challenges to power system economic dispatch problems. One of the major challenges is how to effectively accommodate the wind forecasting errors. Because variations of wind speed directly influence the power output of wind farms, which then causes difficulties in estimating suitable system reserve margin to ensure secure and reliable system operations. As a sequence, high penetration of wind power also cause high potential risks and more difficulties in power system operation. Considering the uncertainty of wind power, this chapter employs a probability based method to address the wind forecast uncertainties involved.

Chapter 7 investigates not only the impact of ETS, but also the RESS on the GENCO's operation in the interactive markets. As introduced in section 2.3.4, fixed feed-in tariffs (FITs) and the fixed premium are the most applied methods as in the categories of RESS. This chapter improves the two-stage decision making model proposed in chapter 5 to include the GENCO's participants not only in EM, CM, and FM, but also in RM. To enhance the solution performance of the model, fuzzy differential evolution (FDE) is applied to solve the optimal outputs of a GENCO in EM effectively. The rest this chapter is organized as follows: In section 7.2, GECNO's participations in these four interactive markets is presented, followed by the overall framework of the proposed decision making model described in section 7.3. Section 7.4 gives the detailed formulation of the proposed decision making model, followed by the FDE introduced in section 7.5. A comprehensive experiment on the proposed model is given in section 7.6 shows a great potential of application of the proposed model to the power system planning and management.

7.2. GENCO's Participation in Multiple Markets

Research efforts have been put into develop the optimal decision making model for GENCOs taking uncertainties of electricity market (EM), carbon market (CM), fuel market (FM) and renewable market (RM) into account individually. A multi-time period electricity network optimization model for GENCOs was presented in [179], which took gas flow, price and storage problems in FM into account. Incorporating a handling scheme to deal with emission constraints, Guo et al. in [180] developed a dynamic economic emission dispatch model of power systems. A typical environmentally constrained power system economic dispatch model, which includes fuel cost minimization and emission constraints, was described in [180]. These studies did not take into account the effects of ETS which play an important role of increasing the /usages of renewable sources. Liu et al. investigated the impacts of both emission trading in CM and renewable energy support schemes in RM on EM's operation [20]. However, emission allowance was treated as a fixed cost so that the trading value was ignored in constructing the decision making models. As to the author's knowledge, no literature addresses the optimal decision making of GENCOs with the effects of EM, FM, CM and RM all taken into account. Following sections 7.2.1 – 7.2.4 demonstrate a GENCO's participation behaviors in the four interactive markets.

7.2.1. Electricity market

The proposed model builds upon an EM, where a GENCO can trade the electricity through either a power pool or bilateral contracts [177]. Accordingly, a GENCO has to decide the trading volumes through the two options respectively. Usually the long term bilateral contracts account for a large share of the total production in order to reduce the uncertainties. The rest is traded though the power pool of which the clearance can be stochastic with fluctuating prices. A GENCO's output from *G* thermal units and *J* wind units $\sum_{g=1}^{G} q_{d,t,g} + \sum_{j=1}^{J} q_{d,t,j}$ at time interval *t* on day *d* is represented by two parts $\xi_{d,t}$ and $\omega_{d,t}$: traded through bilateral contracts and the power pool respectively. Due to uncertainties involved in e.g. market clearance, optimal determination of the volumes of the two parts is a challenging task for GENCOs.

In a power pool, the power pool prices are cleared through a complex balancing process. Although the prices are highly volatile, a GENCO can develop its optimal bidding price and volume in power pool according to the forecast price. The first stage of the proposed model makes decisions in EM, RM, and FM. The optimal volume of electricity output is determined with the bidding price simultaneously. To focus on the planning in multimarket trading, this chapter forecasts the maximum possible output $\lambda_{d,t}$ for the power pool using the method described in [34] based on the historical data. Subject to the constraints in the three markets, FDE is novelly applied to solve the optimal level of the stochastic output $\omega_{d,t} \in [0, \lambda_{d,t}]$ for each hour. In each of FDE iteration, ED is employed to allocate generation of units at minimal possible cost while satisfying all constraints. Here, the classical Lagrange multiplier method can be used to solve the ED problem [202].

7.2.2. Fuel market

According to [24], ETS will increase the usages of wind power so that the power industry's dependence on fossil fuels can be reduced. Simultaneous participations into EM, CM, and RM require a GENCO to build up its own fuel portfolio according to

FM price variations. To guarantee the supply of fuel for different types of generators, a GENCO usually own a certain amount of fuel contracts. For mid and long term planning, GENCOs therefore have to optimize their fuel contracts to hedge against the risks and uncertainties involved in the multimarket environment. For short term planning i.e. daily operation, GENCOs have to decide their fuel usage according to the stochastic clearances in EM with consideration of fluctuating fuel prices, which is one of the focuses of the chapter.

To include the impact of fuel market externalities and simplify the discussion of the model, all the trades in FM are assumed to be similar to the gas market. Therefore, no storage problems are considered in the study. When a GENCO has surplus of fuel in some days it would resell part of the contracts in FMs to avoid extra storage cost. When the contract fuels are not sufficient, a GENCO needs to purchase from FMs to meet the demand. Similar to [177], the fuel consumption function of generator g can be expressed as: $f_g(q_{d,t,g}) = a_g + b_g q_{d,t,g} + c_g q_{d,t,g}^2$, where a_g, b_g, c_g are fuel consumption parameters of thermal generator *g*.

When making decisions in EM, the demand of fuels in FM is obtained. The first stage of the proposed model therefore solves the trading volumes in FM. For generator g at time interval *t* on day *d*, the predicted values of fuel price $p_{d,t,g}^{FM}$, energy price $p_{d,t}^{PEM}$ and the carbon allowance price p_d^{CM} are known before decision making by using e.g. the forecasting tool described in chapter 3. The price prediction in different markets is an important issue but beyond the scope of this chapter.

7.2.3. Carbon market

Under ETS, A GENCO must balance its emission allowances with the generated emissions at the end of the emission commitment period. A unit of allowance is the permission to emit one tonne of CO_2 within the emission commitment period $\{0, C\}$. On the last day of the emission commitment period (i.e. compliance day C), GENCO must pay a penalty price for excessive emissions without allowance as follows:

$$Penalty_C = p_C^{pp} \max[(\sum_{t=1}^{T}\sum_{g=1}^{G} e_g(q_{C,t,g}) + c_C^S) - (x_C + c_C^B), 0] \tag{7-1}$$

where x_C and $\sum_{t=1}^{T}\sum_{g=1}^{G} e_g(q_{C,t,g})$ is the stock of carbon allowances and the accumulated emission at the beginning of day C respectively; c_C^B, c_C^S are units of carbon allowances buying and selling on day C. The penalty price p_C^{pp} is determined before the commitment period based on the national/regional emission cap. It is consistent throughout the whole commitment period. To avoid paying penalty, a GENCO has two options: to operate their units subject to the initial allowances, or to purchase additional carbon allowances in CM during the commitment period.

In contrast to the existing works that consider emissions as a fixed cost in the objective function, the proposed model novelly differentiate GENCO's generated energy into four parts: clean energy, allowed energy, emission energy, and penalty energy. Because clean energy, e.g. wind energy, contributes no carbon emission, the piecewise emission cost of other three parts of energy is shown in Fig.7-1.

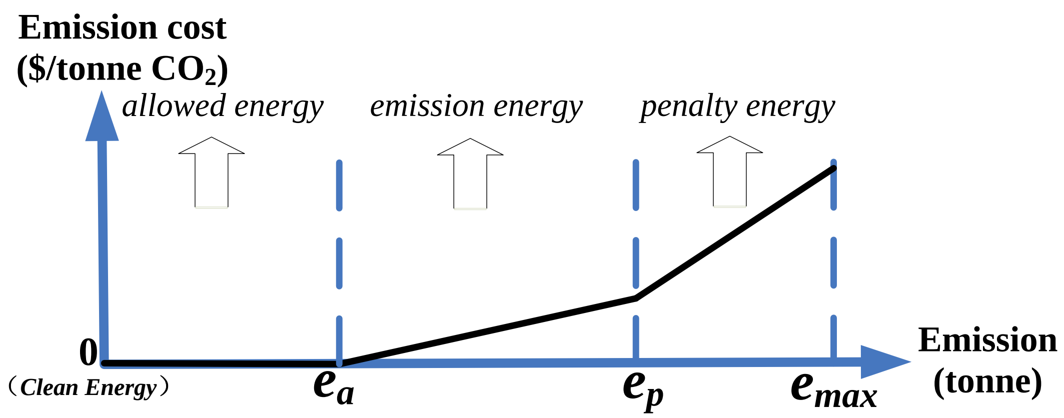

Fig. 7-1 Piecewise emission cost of clean, allowed, emission and penalty energy

In Fig.7-1, the *allowed energy* is the energy generated by thermal units using the stock of carbon allowances. The *emission energy* is produced without pre-assigned allowances so that the GENCO must purchase additional allowances in CM to cover it. The *penalty energy* represents the energy generated without pre-assigned or purchased allowances, and therefore must be penalized. e_{max} is the maximum emission when all the thermal units are producing their maximum power. e_a and e_p are the two emission thresholds varying according to the transactions in CM, which can directly change the GENCO's stock of allowances. The two thresholds can be considered as dynamic constraints in the decision making model. The emission cost on day *d*, $C_d^{co_2}$, is therefore represented by the following piecewise function:

$$C_d^{co_2} = \begin{cases} 0 & \sum_{t=1}^{24}\sum_{g=1}^{G} e_g(q_{d,t,g}) \le e_a \\ \left(\sum_{t=1}^{T}\sum_{g=1}^{G} e_g(q_{d,t,g}) - e_a\right) p_d^{CM} & e_a < \sum_{t=1}^{24}\sum_{g=1}^{G} e_g(q_{d,t,g}) \le e_p \\ e_p p_d^{CM} + \left(\sum_{t=1}^{T}\sum_{g=1}^{G} e_g(q_{d,t,g}) - e_p\right) p_C^{PP} & e_p < \sum_{t=1}^{24}\sum_{g=1}^{G} e_g(q_{d,t,g}) \end{cases} \tag{7-2}$$

where $e_g(q_{d,t,g})$ is the emission function related to the production of thermal generator *g* at time interval *t* on day *d*. p_d^{CM} is the allowance price in CM.

7.2.4. Renewable market

As discussed in section 2.3.4, the most commonly applied RESS methods, namely fixed feed-in tariffs and fixed premium systems, are similar on the whole. Either of them can straightforwardly to encourage advanced planning and stimulate the usage of renewable. Chapter 6 investigated the interaction of RESS and ETS through their respective effects on key electricity market variables (i.e. prices) from the aspect of EM operation. Replicator dynamics algorithm has been employed to simulate the bidding strategies of GENCOs. Although the replicator dynamics algorithm can describe the change trend of individual behaviours so that the agent based model can simulate the EM operation, it is unable to reveal the GENCO's modification in its own decision making. Therefore, this chapter takes into account the effects of implementing these two kinds of RESS into account to analysis the GENCO's behaviour in different markets.

Under a multimarket environment, GENCOs need to consider the market conditions of EM, FM, CM and RM simultaneously. Particularly, the implementation of ETS increases the incremental cost of thermal units. On the contrary, there is little or no incremental cost associated with the wind units. Furthermore, the implementation of the RESS supports GENCOs to produce more from renewable energy such as wind power described considered in this chapter. However, due to the intermittent and stochastic characteristics of wind resource, a GENCOs have has to effectively accommodate the wind forecasting errors so as to maximize its profits. The GENCOs' behaviour will be different according to the mechanism adopted in the RM.

A. Feed-in tariffs

Assuming that the RESS adopts the feed-in tariffs mechanism, that is, all renewable energy would be purchased at a guaranteed price. A fixed price per MWh electricity e.g. 70USD/MWh is paid to the GENCO when the renewable energy is fed into the grid. With a fixed price certainty, a GENCO therefore tends to use all available wind energy according to the forecasting value.

To forecast wind generations, the wind speed can be forecasted using a method such as that described in [203]. Expected available wind generation are then calculated based on the typical wind power curve shown in Fig.7-2, where w_r (MW) is the wind output rated power, v_{in} (m/s), v_r (m/s) and v_{out} (m/s) are the wind cut-in speed, rated speed and cut-out speed, respectively. There is no power output at wind speed v below v_{in} or above

v_{out}; at wind speeds between v_{in} and v_r, the output is equal to the product of the mass flow rate of the wind, m_W, and $v^2/2$. Assuming constant blade area or ducted flow, the continuity equation states that $m_W=\rho Av$, where ρ is the density of the air in kg/m^3, A is the blade area in m^2. The total wind power, in MW, becomes $P_W=(m_W v^2)/2=(\rho Av^3)/2$. As a result, wind power output w can be described as;

$$\begin{cases} W = 0, & V < v_{in} \text{ or } V > v_{out} \\ W = \dfrac{1}{2}\rho AV^3, & v_{in} \le V \le v_r \\ W = w_r, & v_r \le V \le v_{out} \end{cases} \tag{7-3}$$

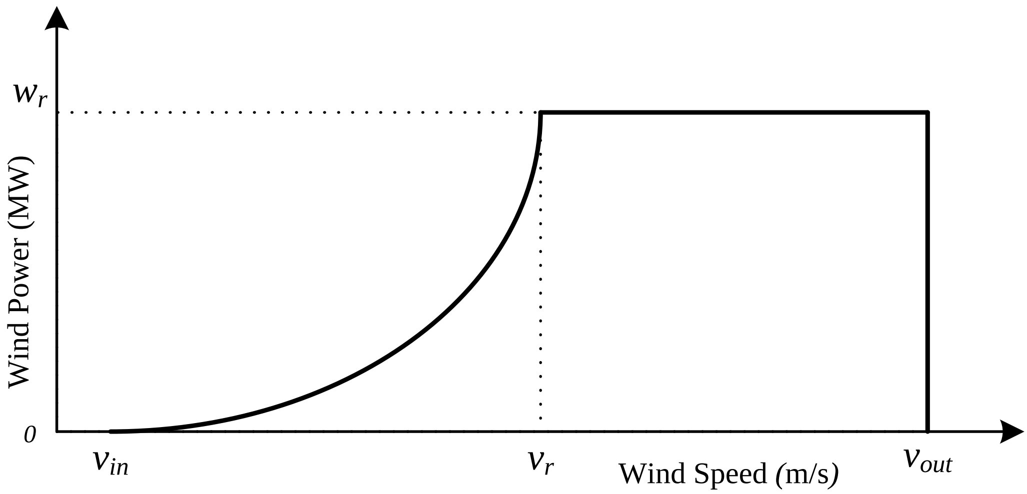

Fig. 7-2 Typical wind turbine power curve

B. Fixed premium system

It is a different case when a fixed premium system is adopted in the RM. For a fixed premium system, the rate added to the electricity price is fixed. The difference between feed-in tariffs and fixed premium system is that the price of purchasing renewable energy is fixed in the former and volatile in the latter. For the renewable plant (e.g. wind farm) owner, the total price received per MWh (e.g. 16USD/MWh) in the premium scheme (electricity price plus the premium) is less predictable than that under a feed-in tariff, since this depends on a volatile electricity price.

As the revenue in RM is not yet guaranteed, there might be some hours that the revenue is too low to recover the cost relating to the forecast error of wind energy outputs. To enable a GENCO with wind farm to make a trade-off decision on the volatile revenue in the fixed premium system and the cost relating to the forecast errors, a probability based method is developed to characterize the natural of wind speed. Because of the uncertainty of the availability of wind energy at any given time, factors for overestimation and underestimation of available wind energy must be included in the model. An approach using a linear wind power output curve was proposed in J. Hetzer and D. C. Yu's work in reference [204]. To predict the wind energy more precisely, the approach has been improved in this chapter, using a nonlinear wind power output curve as shown in Fig.7-2.

To describe wind speed frequency curve, the Weibull distribution is the most widely accepted density function [205-207]. An extensive review of various probability density functions of wind speed was provided in reference [207], which indicated that the two-parameter Weibull distribution is the widely accepted model. Using a two-parameter Weibull distribution, cumulative distribution function (CDF), $F_V(v)$, and probability density function (PDF), $f_V(v)$, of the wind speed random variable V are as follows:

$$F_V(v) = 1 - \exp\left[-\left(\frac{v}{c}\right)^k\right] \tag{7-4}$$

$$f_V(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} \exp\left[-\left(\frac{v}{c}\right)^k\right] \tag{7-5}$$

where $k>0$ is the shape parameter, $c>0$ is the scale parameter. According to (7-3), three portions of the wind power output random variable W can be analyzed and the corresponding probabilities $\Pr(\bullet)$ can be calculated, respectively.

1) For $V < v_{in}$ *or* $V > v_{out}$,

$$\begin{aligned}\Pr(W=0) &= \Pr(v < v_{in}) + \Pr(v > v_{out}) \\ &= F_V(v_{in}) + \left[1 - F_V(v_{out})\right] = 1 - \exp\left[-\left(\frac{v_{in}}{c}\right)^k\right] + \exp\left[-\left(\frac{v_{out}}{c}\right)^k\right]\end{aligned} \tag{7-6}$$

2) For $v_{in} \le V \le v_r$,

$$F_W(w) = \Pr\{W \le w\} = \Pr\left\{W = \frac{1}{2}\rho A v^3 \le w\right\} = \Pr\left\{v \le \left(\frac{2w}{\rho A}\right)^{\frac{1}{3}}\right\} = F_V\left[\left(\frac{2w}{\rho A}\right)^{\frac{1}{3}}\right] \tag{7-7}$$

According to the chain rule for derivatives, the PDF, $f_W(w)$, can be obtained by differentiating $F_W(w)$ with respect to *w*, where $u = \left(\frac{2w}{\rho A}\right)^{\frac{1}{3}}$.

$$f_W(w) = \frac{dF_W(w)}{dw} = \frac{dF_W(w)}{du}\frac{du}{dw} = \frac{k}{3c^k}\left(\frac{2}{\rho A}\right)^{\frac{k}{3}} w^{\left(\frac{k}{3}-1\right)} \exp\left[-\frac{1}{c^k}\left(\frac{2w}{\rho A}\right)^{\frac{k}{3}}\right] \tag{7-8}$$

3) For $v_r < V \le v_{out}$,

$$\Pr(W = w_r) = \Pr(v_r \le v \le v_{out}) = F_V(v_{out}) - F_V(v_r) = \exp\left[-\left(\frac{v_r}{c}\right)^k\right] - \exp\left[-\left(\frac{v_{out}}{c}\right)^k\right] \tag{7-9}$$

Due to the uncertainty of wind power forecasts, the predictions normally have some errors. To address the uncertainties in wind power generation prediction so as a GENCO can optimize its decisions in RM subject to the fluctuated electricity prices in EM, two penalty costs are formulated in (7-10) and (7-11) respectively. The underestimation situation occurs if the actual generated wind power is more than the predicted amount. The surplus wind power is usually sold to adjacent utilities, or by fast re-dispatch and automatic gain control (AGC), the output of non-wind generators is correspondingly reduced [204]. Only if this cannot be achieved, then dummy load resistors need to be connected to “waste” the surplus energy. Obviously, these practicalities can be modeled by a simple underestimation penalty cost function. However, if the wind farms entirely belong to the GENCO, the underestimation penalty cost may be ignored. On the other hand, an overestimation penalty cost is paid for purchasing reserve power from other sources. Both penalty costs are included in this chapter in the most general sense to make it applicable to all situation, regardless of how the share of the generation facilities.

It is assumed that either the underestimation or overestimation penalty cost is linearly related to the difference between the available wind power $W_{d,t,j}$ and the scheduled wind power $q_{d,t,j}$. Considering the Weibull PDF of wind variation as descried in (7-5), a random variable available representing the available wind power from the wind turbine *j* at time interval *t* on day *d*, $W_{d,t,j}$, is assumed with a value in the range of $0 \le W_{d,t,j} \le w_{r,j}$ and varying with the given PDF. According to the definition of expected value of an arbitrary function [204], the expected underestimation penalty cost for the wind turbine *j* is assumed as follows,

$$\begin{aligned} E\left[C_{u,j}\max\left(W_{d,t,j}-q_{d,t,j},0\right)\right] &= C_{u,j}\left(W_{d,t,j}-q_{d,t,j}\right) \\ &= C_{u,j}\left[\int_{q_{d,t,j}}^{w_{r,j}} w_{a,j} f_W\left(w\right)dw - q_{d,t,j}\int_{q_{d,t,j}}^{w_{r,j}} f_W\left(w\right)dw\right] \end{aligned} \tag{7-10}$$

where $w_{d,t,j}, q_{d,t,j}, w_{r,j}$ is the actual power, predicted power, and the rated power of the wind turbine *j*, respectively. $C_{u,j}$ is the underestimation penalty cost for the wind turbine *j*.

Similarly, the expected overestimation cost for reserve requirement is an integral over the PDF of the wind power random variable $W_{d,t,j}$ with a value in the range of

$0 \le W_{d,t,j} \le q_{d,t,j}$. The difference between (7-10) and (7-11) is that the latter is a cost due to the available wind power being less than the scheduled wind power.

$$\begin{aligned} E\left[C_{o,j}\max\left(q_{d,t,j}-W_{d,t,j},0\right)\right] &= C_{o,j}\left(q_{d,t,j}-W_{d,t,j}\right) \\ &= C_{o,j}\left[q_{d,t,j}\int_0^{q_{d,t,j}} f_W\left(w\right)dw - \int_0^{q_{d,t,j}} w_{d,t,j}\,f_W\left(w\right)dw\right] \end{aligned} \tag{7-11}$$

where $C_{o,j}$ is the underestimation penalty cost for the wind turbine *j*. Equations (7-10) and (7-11) can be solved through the wind power probability stetted up by equations (7-6) - (7-9). Through this improved technology, the proposed model can characterize wind uncertainty and make its decision in RM. In general, losses are ignored in the model; however, they could be added in the system load and losses term, if necessary.

7.3. Hierarchical Decision Making Framework

The proposed decision making model enables a GENCO to maximize its profit through proper decision making in a hierarchical structure. Without loss of generalities, all generation units of the GENCO are assumed online during the planning period. The unit commitment that actually determines on-off status of units can be integrated into the proposed model in our future work.

As shown in Fig.7-3, the decision making model decomposes the planning into a four-layer hierarchical structure. At each planning level, a GENCO's expected output is forecasted based on the corresponding historical data [208] and then the output of a higher level is evenly distributed to each time span of its sublevel (termed as average dispatch). As a result, information of the sublevel including fuel consumptions and emissions can be obtained. The average dispatch at the higher levels helps a GENCO to make a rational decision under multimarket environment to benefit the long term interests. Through this hierarchical framework, the planning and decision making at the high levels facilitate a GENCO's market operations and profit making, whereas this chapter focuses on the short term decision making.

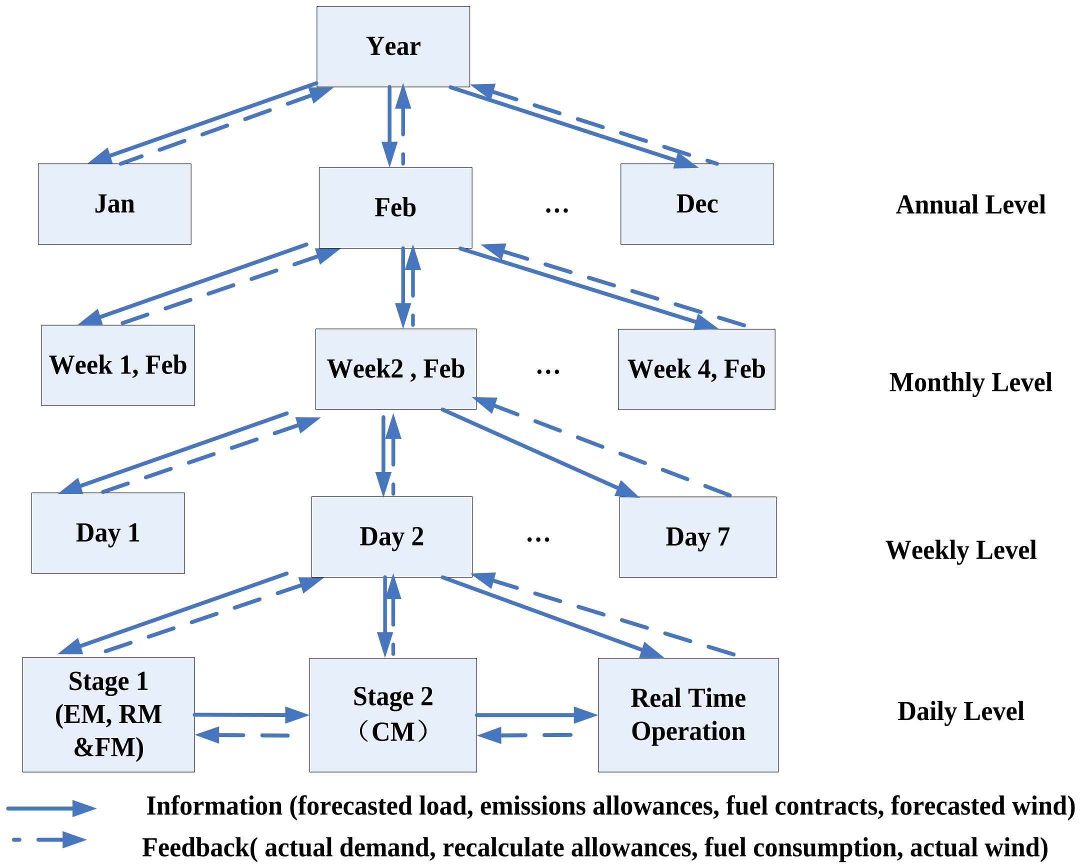

Fig. 7-3 Hierarchical decision making model

At the daily level, there are two stages in the planning which interact through the change of accumulated emission and stock of carbon allowances introduced. A GENCO's decision makings are dynamically affected by these changes due to (7-2). The stock of carbon allowances are composed of two parts: initial allowance and purchased allowance (trade or auction from a carbon market). Generally, initial allowances are assigned to a GENCO annually through either a grandfathering, output-based allocation or an auction based method [22]. Any trades in CM directly change the stock of carbon allowances so that e_a varies accordingly, while the allowances a GENCO can acquire from CM are stochastic and closely related to the market conditions. To obtain e_p, historical trading data in previous commitment periods are fitted into a lognormal distribution at the long term levels, i.e. annual and monthly. The maximum possible allowances a GENCO can acquire during the current emission commitment period are firstly obtained using the Monte Carlo simulation with a given risk factor before the planning period. The application of Monte Carlo simulation enables a GENCO to know the maximum possible allowances which it can acquire before decision making. Notice that Monte Carlo simulation does not need to be included in the daily decision making process. Then the total estimated allowances, including the stock of allowances and the allowances which a GENCO can possibly purchase are dispatched to the monthly or weekly level shown in Fig.7-3. Based on the updated stock of carbon allowance, the proposed model solves the optimal electricity production by FDE so that the decisions for EM, RM and FM can be obtained simultaneously in stage 1. Following is stage 2, in which GENCO not only has to maximize the trading profits in CM, but also need to balance the allowances with the produced emissions by the end of the planning horizon in the most cost efficient way. The decision in stage 2 directly changes the GENCO's stock in the next planning day, and also the emission thresholds in (7-2). This is a complicated problem while the proposed model creatively considers the emission as a dynamic constraint and optimizes the decision in each market. The differences between the planning (stage 1 and stage 2) and the operations in real time are used to update information in the next planning period at each level.

7.4. Model Formulation

7.4.1. Revenues from multiple markets

Assume a GENCO has I long term bilateral energy contracts with its customers. Each contract i consists of the capacity part (which reserve the GENCO's capacity to provide power) and the energy part. Each part corresponds to a specified contract price $p_{d,t}^{CC}$ and $p_{d,t}^{EC}$, respectively. The revenue from the bilateral contracts R^{BEM} is represented as:

$$R^{BEM} = \sum_{d=d_0}^{D} \sum_{t=1}^{T} \left[p_{d,t}^{CC} \sum_{i=1}^{I} Q_{d,t,i} + p_{d,t}^{EC} \sum_{i=1}^{I} \min\left(l_{d,t,i}, Q_{d,t,i} \right) \right] \tag{7-12}$$

where $l_{d,t,i}$ is the predicted load of the customer and $Q_{d,t,i}$ is the capacity of bilateral contract *i* at time interval *t* on day *d*.

The revenue from selling electricity in power pool R^{PEM} is another income of a GENCO. The proposed model solves optimal $q_{d,t,g}$ for each thermal units and $q_{d,t,\mathrm{j}}$ for each wind turbine using FDE and therefore its revenue is

$$R^{PEM} = \sum_{d=d_0}^{D} \sum_{t=1}^{T} \left\{ p_{d,t}^{PEM} \max\left[\sum_{g=1}^{G} q_{d,t,g} + \sum_{j=1}^{J} q_{d,t,j} - \sum_{i=1}^{I} \min\left(l_{d,t,i}, Q_{d,t,i} \right), 0 \right] \right\} \tag{7-13}$$

In FM, a GENCO has certain amounts of heat energy $Q_{d,t,g}^{FM}$ from the long term fuel contract for each generator *g* at time interval *t* on day *d*. The revenue from trading in FM R^{FM} is:

$$R^{FM} = \sum_{d=d_0}^{D} \sum_{t=1}^{T} \sum_{g}^{G} \left[p_{d,t,g}^{FMS} \max\left(Q_{d,t,g}^{FM} - f_g\,(q_{d,t,g}), 0 \right) \right] \tag{7-14}$$

where $p_{d,t,g}^{FMS}$ is the fuel price calculated based on the predicted benchmark price $p_{d,t,g}^{FM}$ of the fuel market: $p_{d,t,g}^{FMS} = \beta p_{d,t,g}^{FM}$.

In CM, a GENCO would aim at maximizing the profits while balancing its allowances with the generated emission. The second stage of the proposed model optimizes the selling and purchasing allowances (c_d^S and c_d^B) in CM on day *d*. Considering the market price and the accumulated and forecasted emissions within the planning horizon, the revenue in CM is computed as:

$$R^{CM}=\sum_{d=d_0}^{D}\left(I_d^{CMS}p_d^{CM}c_d^S\right) \tag{7-15}$$

Excessive trades are limited through the CM selling index I_d^{CMS} which takes the allowance price variations into account:

$$I_d^{CMS}=\begin{cases}\beta, & if\ \dfrac{\mu(p_{d+1:D}^{CM})-p_d^{CM}}{p_d^{CM}}<r_1\\ 0, & if\ \dfrac{\mu(p_{d+1:D}^{CM})-p_d^{CM}}{p_d^{CM}}\geq r_1\end{cases} \tag{7-16}$$

where $\mu(p_{d+1:D}^{CM})$ is the mean value of the allowance price from day d+1 to day D, which is forecasted by [13]; β is the penalty factor within [0, 1]; r_1 is the risk factor of a GENCO within [0, 1], which is used to limit excessive selling.

In RM, a GENCO is expected to decide the wind power output according to the employed RESS mechanisms as discussed in section 7.2.4. The revenue of a GENCO in feed-in-tariffs or fix premium system is:

$$R^{RM}=\begin{cases}p_{d,t}^{FIT}\sum_{d=d_0}^{D}\sum_{t=1}^{T}\sum_{j=1}^{J}q_{d,t,j}, & \text{Feed-in-tarrifs}\\ (p_{d,t}^{FP}-p_{d,t}^{PEM})\sum_{d=d_0}^{D}\sum_{t=1}^{T}\sum_{j=1}^{J}q_{d,t,j}, & \text{Fix premium}\end{cases} \tag{7-17}$$

where $p_{d,t}^{FIT}$ is the fixed premium in RM. If the feed-in-tariffs is adopted, the price of each electricity produced by wind power is fixed in $p_{d,t}^{FP}$.

7.4.2. Costs from multiple markets

In EM, Power pool features with volatile spot prices and stochastic demand. When the spot price is lower than a certain level, a GENCO is able to fulfill the extra demand by purchasing a part of electricity from the power pool instead of producing. However, a GENCO needs to produce certain amount of electricity due to the physical constrains and the output limitations of generators. At some time intervals, the contract loads cannot be fulfilled because of the physical limits such as ramp up/down rate. In this case, a GENCO needs to purchase power from the spot market. The cost of trading in power pool C^{PEM} can be expressed as follows:

$$C^{PEM} = \sum_{d=d_0}^{D} \sum_{t=1}^{T} p_{d,t}^{PEM} \left\{ \begin{aligned} & I_{d,t}^{EM} \max\left[0, \sum_{i}^{I} \min\left(l_{d,t,i}, Q_{d,t,i}\right) - \max\left(G_g^{\min}, q_{d,t-1,g} - \Delta G_g^D\right)\right] \\ & +(1\text{-}I_{d,t}^{EM}) \max\left[0, \sum_{i=1}^{I} \min\left(l_{d,t,i}, Q_{d,t,i}\right) - \sum_{g=1}^{G} q_{d,t,g}\right] \end{aligned} \right\} \quad (7\text{-}18)$$

where $\sum_{g=1}^{G} G_g^{\min}$ is the total minimum output of the GENCO for all thermal units. $I_{d,t}^{EM}$ is an index function, indicating whether a GENCO should buy part of power from the power pool or not.

$$I_{d,t}^{EM} = \begin{cases} 1, & p_{d,t}^{PEM} \sum_{g=1}^{G} q_{d,t,g} < \sum_{g=1}^{G} p_{d,t,g}^{FMB} f_g\left(q_{d,t,g}\right) + C_d^{co_2} \\ 0, & otherwise \end{cases} \quad (7\text{-}19)$$

where the emission cost, $C_d^{co_2}$, is computed according to (7-2).

In FM, the price of the long term fuel contract for generator g, $P_{d,t,g}^{LFM}$, is known before the planning period . The cost of the long term contracts, C^{LFM}, can be expressed as follows:

$$C^{LFM} = \sum_{d=d_0}^{D} \sum_{t=1}^{T} \sum_{g=1}^{G} \left[p_{d,t,g}^{LFM} Q_{d,t,g}^{FM} \right] \quad (7\text{-}20)$$

A GENCO needs to purchase fuel to meet the demand of the specified generators when the heat energy of the long term contract is not sufficient. The cost of fuel purchasing C^{FM} is expressed as follows:

$$C^{FM} = \sum_{d=d_0}^{D} \sum_{t=1}^{T} \sum_{g}^{G} p_{d,t,g}^{FMB} \left[\max\left(f_g\,(q_{d,t,g}) - Q_{d,t,g}^{FM}, 0 \right) \right] \tag{7-21}$$

where $I_{d,t}^{EM}$ is an index function, indicating whether a GENCO should buy part of power from the power pool or not.

In CM, a GENCO, if necessary, can purchase c_d^B emission allowance when the allowance price p_d^{CM} is relatively low. The cost of a GENCO in CM is:

$$C^{CM} = \sum_{d=d_0}^{D} \left[I_d^{CMB} p_d^{CM} c_d^B \right] \tag{7-22}$$

The CM buying index I_d^{CMB} suggests purchasing allowances when the current price is lower than the mean value of the future prices at a certain level, which is expressed as follows:

$$I_d^{CMB} = \begin{cases} \beta^{-1}, & if\ \dfrac{\mu(p_{d+1:D}^{CM}) - p_d^{CM}}{p_d^{CM}} > r_1 + r_2 \\ 0, & if\ \dfrac{\mu(p_{d+1:D}^{CM}) - p_d^{CM}}{p_d^{CM}} \le r_1 + r_2 \end{cases} \tag{7-23}$$

where the risk factor r_2 is used to control excessive purchasing.

As discussed in section 7.2.4, the overestimation penalty cost and overestimation penalty cost are applied to assist obtaining an optimum allocation of power output among the available generators. A GENCO tends to use all available wind energy according to the forecasting value when fix-feed-in tariffs in adopted. With a fixed price certainty, the cost C^{RM} can be ignored. When the fixed premium system is applied, the cost C^{RM} is calculated as follows:

$$C^{RM} = \sum_{j=1}^{J} E\left[C_{u,j} \max\left(W_{d,t,j} - q_{d,t,j}, 0 \right) \right] + \sum_{j=1}^{J} E\left[C_{o,j} \max\left(q_{d,t,j} - W_{d,t,j}, 0 \right) \right] \tag{7-24}$$

7.4.3. The two stages of the decision making model

In the proposed decision making model, there are two consecutive stages which interact through the accumulated emission level and stock of carbon allowances which has been introduced in Section 7.3. The model aims at making decision to maximize the total profit Γ_D of a GENCO during the whole planning period $d = \{d_0, D\}$. It can be expressed as follows:

$$\Gamma_D = (R^{BEM} + R^{PEM} + R^{CM} + R^{FM} + R^{RM}) - (C^{CM} + C^{LFM} + C^{FM} + C^{PEM} + C^{RM}) \quad (7\text{-}25)$$

In the first stage, the stochastic output $\omega_{d,t}$ is solved by FDE, together with scheduled wind generator output $q_{d,t,j}$ and the $q_{d,t,g}$ dispatched to all thermal units. For all units on the current planning day *d**, the stage 1 of the model is presented as follow:

$$S^1_{d^*}(\omega_{d,t}, q_{d,t,j}, q_{d,t,g}) = \begin{cases} \max \Gamma_D(\omega_{d,t}, q_{d,t,j}, q_{d,t,g}) \\ s.t. \;\; q_{d,t,g} \le \min\left(G_g^{\max}, q_{d,t-1,g} + \Delta G_g^U\right) \\ \qquad q_{d,t,g} \ge \max\left(G_g^{\min}, q_{d,t-1,g} - \Delta G_g^D\right) \\ \qquad 0 \le q_{d,t,j} \le w_{r,j} \\ \qquad \sum_{g=1}^{G} G_g^{\max} \ge \sum_{i=1}^{I} \max\left(l_{d,t,i}, Q_{d,t,i}\right) + R_{d,t} \end{cases} \quad (7\text{-}26)$$

To account for the physical constraints of each generator, power productions $q_{d,t,g}$ are subjected to the maximum generation outputs $G_g^{\max}$, minimum generation outputs $G_g^{\min}$, ramp up and ramp down rates $\Delta G_g^U, \Delta G_g^D$ constraints. The scheduled wind power is subjected to the rated power (maximum energy output of each wind generator). Spinning reserve $R_{d,t}$ is required to be fulfilled by a GENCO as a whole while all thermal generation units are assumed online during the planning period. Therefore units start-up and related costs can be ignored. Based on all units' electricity production, the trading strategies in EM and FM can be obtained in stage 1.

In the second stage, $S_{d^*}^2(c_d^B, c_d^S)$ is used to determine the trading strategy in CM on the current planning day *d**. The second stage of the model is expressed as follows:

$$S_{d^*}^2(c_d^B, c_d^S) = \begin{cases} \max\left\{\Gamma_D(c_d^B, c_d^S) - Penalty_C \times \left[1 - \min\left(C-d, 1\right)\right]\right\} \\ s.t. \quad (x_D + c_D^B) - (\sum_{t=1}^{24}\sum_{g=1}^{G} e_g(q_{D,t,g}) + c_D^S) \geq 0 \\ \qquad c_d^B = \max\left[\sum_{d=d^*}^{D}\sum_{t=1}^{24}\sum_{g=1}^{G} e_g(q_{d,t,g}) - x_d, 0\right] \\ \qquad c_d^S = \max\left[x_d - \sum_{d=d^*}^{D}\sum_{t=1}^{24}\sum_{g=1}^{G} e_g(q_{d,t,g}), 0\right] \\ \qquad c_d^B \times c_d^S = 0 \end{cases} \tag{7-27}$$

where $x_d = x_{d-1} - \sum_{t=1}^{24}\sum_{g=1}^{G} e_g(q_{d-1,t,g}) + c_{d-1}^B - c_{d-1}^S$ is the stock of a GENCO at the beginning of day *d*. At the beginning of the planning period d=d_0, an initial allocated allowance is assumed known from the higher level. The constraints $C_d^B \times C_d^S = 0$ disallow buying and selling allowance simultaneously. The penalty has to be paid on the compliance day *C* if a GENCO cannot match its allowance with the generated emission. The trading volume in CM is solved based on the forecasts of future market prices and emission levels. Generally, the trading profit during the whole planning period is maximized through the volume of allowance traded on day *d**. This is because for periods $1\ldots d^*-1$, the decision variables and stochastic parameters of the model are considered fixed to their already realized values. Thus, the optimization considers variations in the variables and stochastic parameters only for periods *d*… D*.

7.4.4. Solution logic of the decision making model

As discussed in section 7.2.1, a GENCO needs to deicide its stochastic output $\omega_{d,t}$ and arrange all generators' production aiming at maximizing the profit using (7-26) in stage 1. FDE is suitable to solve this non-deterministic polynomial-time hard combination optimization problem. The trading strategies in EM and FM are then determined after all units' electricity production are solved. In stage 2, the decision of allowance trading in CM can be made according to (7-27). The procedures of solving the decision making model are depicted in Fig.7-4.

The model firstly read the input data, including the forecasted spot prices of EM, CM and FM, the contract demand, the maximum possible output for the power pool, and the forecasted wind speed. After FDE initializes the population, fuzzy control, mutation, crossover, and selection have been implemented to generate trial individuals. In stage 1 of Fig.7-4, the control parameters F and Cr are adaptively adjusted by fuzzy logic (the block on the right hand side) during the DE iteration process. Each individual represents the value of outputs in each time interval. Economic dispatch (ED) is conducted for all generators in each individual time interval and the corresponding profit is obtained. If the model converges or the maximum iteration number is reached, the optimal decision of the production process is obtained for this time interval. The above mentioned process computes 24 optimal electricity production decisions in stage 1. The optimal trading volumes in EM and FM are computed according to (7-13) and (7-18), according to (7-14) and (7-21), respectively. When the RM adopts Feed-in-tariff system, the wind output is schedule as its forecasted value based on method introduced in [203]. The decision of wind energy output can be made with the Weibull distribution stetted up by equations (7-6) - (7-9). Based on the decisions made in the first stage, the second stage solves the trading strategy in CM according to (7-27) for each planning day.

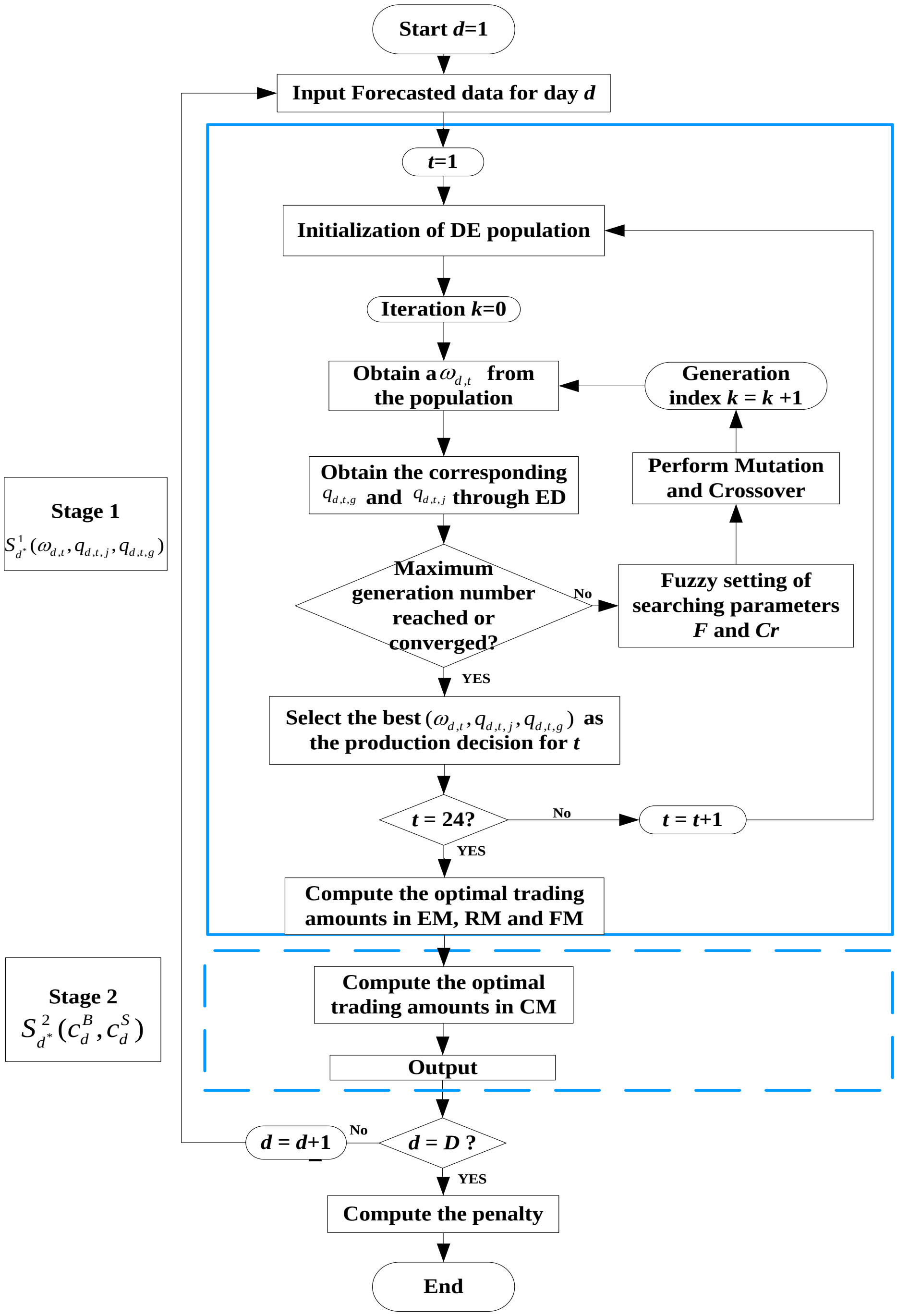

Fig. 7-4 Decision making model of GENCO

7.5. Fuzzy Differential Evolution

Differential Evolution (DE) can be used to solve stochastic problems effectively. Its efficiency is affected significantly by its control parameters *F* and *Cr* [183]. FDE [209] improves the performance of DE by using the fuzzy logic to adjust these parameters adaptively. Because of its efficiency compared with the DE, FDE is therefore applied to solve the proposed model.

FDE has the following steps: initialization, fuzzy control, mutation, crossover, and selection.

1) *Initialization*: each of *N* individuals is a *P* dimensional vector within the whole population Π of dimension *NP*. The structure of the whole population is shown as:

$$[\Pi]=\begin{bmatrix}\Pi_{11} & \Pi_{12} & \dots & \Pi_{1P}\\ \Pi_{21} & \Pi_{22} & \dots & \Pi_{2P}\\ \vdots & \vdots & \vdots & \vdots\\ \Pi_{N1} & \Pi_{N2} & \dots & \Pi_{NP}\end{bmatrix} \tag{7-28}$$

FDE randomly generates values from dimension *J* of the individual $X_{j,k,l}$ within the lower and upper limits of the dimension, where *j* is the dimension index, *k* is individual index and *l* is generation index.

2) *Fuzzy Control*:

In a DE process, *F* is the mutation searching factor whose value is initially chosen as $F\in[0.5,1]$, and *Cr* is the crossover factor whose value is initially chosen as $Cr\in[0.8,1]$. The purpose of using fuzzy logic as shown in Fig.7-5 is to make the DE's control parameters adaptively adjusted in the evolution process. $FC=\sqrt{\frac{1}{NP}\sum_{k=1}^{NP}\left(f(X_{j,k,l})-f(X_{j,k,l-1})\right)^2}$ and $PC=\sqrt{\frac{1}{NP}\sum_{k=1}^{NP}\sum_{j=1}^{J}\left(X_{j,k,l}-X_{j,k,l-1}\right)^2}$ are inputted to control the fuzzy logic adptively, where $f(X_{j,k,l})$ is the objective function value.

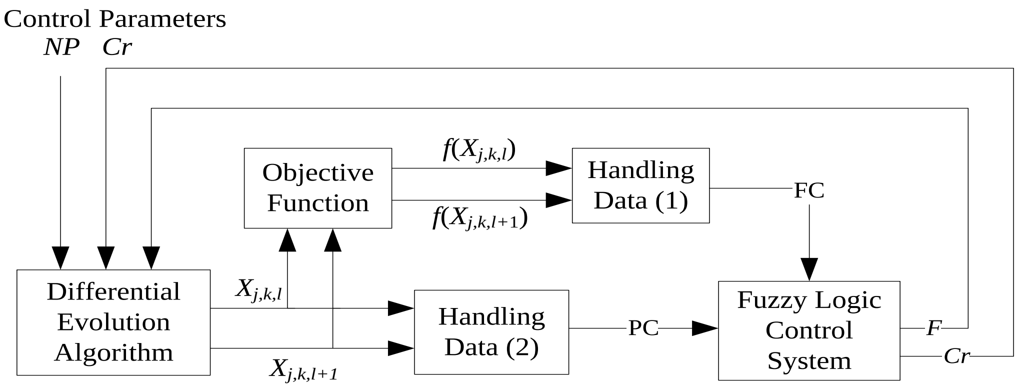

Fig. 7-5 Control diagram of fuzzy setting

Values of the fuzzy variables v_{11}, v_{12}, v_{21} and v_{22} in (7-29) are used in the fuzzy controller to map the inputs of PC and FC onto outputs *F* and *Cr*. Their values are assigned as membership grades in three fuzzy sets as small (S), medium (M), and big (B): 0.05, 0.5 and 0.9 for v_{11}; 0.01, 0.5 and 0.9 for v_{12}; 0.1, 0.8 and 1.5 for v_{21}; 0.1, 0.8 and 1.5 for v_{22}, 0.3, 0.6 and 0.9 for *F*, 0.4, 0.7 and 1.0 for *Cr*. Among a set of membership functions, Gaussian curve membership function is chosen during the fuzzy setting process.

$$\begin{aligned} v_{11} &= 1-(1+PC)\times e^{-PC} \\ v_{12} &= 1-(1+FC)\times e^{-PC} \\ v_{21} &= 2-(1-(1+PC)\times e^{-PC}) \\ v_{22} &= 2-(1-(1+FC)\times e^{-PC}) \end{aligned} \tag{7-29}$$

Table 7-1 Fuzzy rules of the proposed model

RULES	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***
V_{11}, V_{21}	S	S	S	M	M	M	B	B	B
V_{12}, V_{22}	S	M	B	S	M	B	S	M	B
F, CR	S	M	B	M	M	B	B	B	B

Based on the above parameters and fuzzy sets, IF/THEN fuzzy rules are established to formulate the conditional statements of the fuzzy logic. The fuzzy rules are shown in Table 7-1. Each fuzzy rule *r* in table 1 represents a fuzzy relation $R_{[(FC,PC),(F,Cr)]}$. The fuzzy control is used to map from the given inputs to an output. Mathematically, it can be expressed as (7-30).

$$\begin{aligned} R_{[(FC,PC),(F,Cr)]} &= \int_{(FC,PC)} \int_{(F,Cr)} \mu_R[(FC,PC),(F,Cr)] \\ &= \int_{(FC,PC)} \int_{(F,Cr)} \min[\mu_1(FC),\mu_2(PC),\mu_3(F,Cr)] \end{aligned} \tag{7-30}$$

where μ_1 and μ_2 are the membership functions of the input parameters, μ_3 is the membership function of the output parameter. μ_R is the membership function of the fuzzy relation. Combining all the rules, the fuzzy set described by the rule set can be obtained as:

$$\begin{aligned} &\mu_R : FC \times PC \times (F,Cr) \\ &[FC,PC,(F,Cr)] \mapsto \bigcup_{r=1}^{R} [\mu_r^{(FC)}(FC) \cap \mu_r^{(PC)}(PC) \cap \mu_r^{(F,Cr)}(F,Cr)] \end{aligned} \tag{7-31}$$

Using minimum for the intersection and maximum for the union, we have:

$$\begin{aligned} &\mu_R : FC \times PC \times (F,Cr) \\ &[FC,PC,(F,Cr)] \mapsto \max_{r \in R} \left\{ \min[\mu_r^{(FC)}(FC) \cap \mu_r^{(PC)}(PC) \cap \mu_r^{(F,Cr)}(F,Cr)] \right\} \end{aligned} \tag{7-32}$$

For a crisp input value of *FC* and *PC*, the fuzzy output value is:

$$\mu_{R,FC,PC}^{output} : (F,Cr) \mapsto \mu_r[FC,PC,(F,Cr)] \tag{7-33}$$

Finally, the fuzzy output value must be aggregated into a crisp output value. In this chapter, the center of area method (COA) [16] is used to do the defuzzification:

$$COA(\mu_{R,F,Cr}^{output}) = \frac{\int_{(F,Cr)} \mu_{R,FC,PC}^{output} \cdot (F,Cr)\, d(F,Cr)}{\int_{(F,Cr)} \mu_{R,FC,PC}^{output} \cdot d(F,Cr)} \tag{7-34}$$

3) *Mutation*: It is executed to randomly choose three different individuals to produce a mutant individual $V_{j,k,l}$ according to:

$$V_{j,k,l} = X_{j,a,l} + F\left(X_{j,b,l} - X_{j,c,l}\right) \tag{7-35}$$

where a, b and c are random numbers within [1, *NP*]; F is the mutation searching factor which is adaptively obtained in the fuzzy setting process.

4) *Crossover*: DE creates a different individual called the trial individual, based on the original individual $X_{j,k,l}$ and the mutant individual $V_{j,k,l}$. The crossover is expressed as:

$$U_{j,k,l} = \begin{cases} V_{j,k,l} & if\ rand_j\left(0,1\right) \le Cr\ or\ j = j_{rand} \\ X_{j,k,l} & otherwise \end{cases} \tag{7-36}$$

where Cr is the crossover searching factor which is adaptively obtained in the fuzzy setting process.

5) *Selection*: DE produces individuals for the next generation. The original individual and the trial individual are compared using their objective function values $f(X_{j,k,l})$. The one with the larger value is selected for the next generation.

The four steps (mutation, fuzzy settings, crossover, and selection) repeat until an acceptable solution is obtained or the predefined maximum iteration number is reached.

7.6. Experiments on The Proposed Model

To demonstrate the effectiveness and performance of the proposed algorithm, a case study is carried out on a typical GENCO which owns one wind farm and six thermal generators, including two coal-fired, two gas-fired, and two oil-fired units. The details of the generators are provided in Table 7-2. The entire planning period $d = \{d_0, D\}$ is assumed to be the week before the compliance day C ($d_0 = C - 6$, $D = C$). Each planning day d is divided into 24 intervals (T = 24).

Table 7-2 Generation limits, fuel parameters and emission factors

	Unit1	Unit2	Unit3	Unit4	Unit5	Unit6	Unit7
$G_g^{\min}$ (MW)	10	20	55	60	100	150	0
$G_g^{\max}$ (MW)	100	130	120	180	220	455	90
a_g (MMBtu)	129.97	318.18	126	240	177	480	0
b_g (MMBtu/MW)	32.6	0. 26	8.65	7.74	13.51	7.4	0
c_g (MMBtu/MW^2)	0.0011	0.06	0.0028	0.0032	0.0004	0.0002	0
Ramp up/down (MW)	50	30	40	75	70	60	60
Emission factor (kg/MMBtu)	54.01	95.52	74.54	74.54	54.01	95.52	0
Fuel Type	Gas	Coal	Oil	Oil	Gas	Coal	Wind

Table 7-3 Forecasted upper bound of hourly output

Hourly Output (MWh)	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
8	700.6	623.7	571.3	603.0	590.0	588.2	605.7
16	720.7	651.5	617.1	628.7	619.6	628.9	652.0
24	552.4	485.4	471.7	453.7	436.7	478.3	484.4

Note: Owing to limited space, only the data of hours 8, 16 and 24 are listed

Table 7-4 Forecasted value of prices in EM

Hourly Price ($/MWh)	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
8	28.6	33.0	37.1	40.1	39.5	42.0	44.0
16	36.8	50.3	58.5	82.5	47.4	38.9	50.6
24	30.3	36.3	36.7	37.5	36.9	36.2	45.1

Note: Owing to limited space, only the data of hours 8, 16 and 24 are listed

Table 7-5 Forecasted and actual prices in FM

Price ($/MMBtu)	Coal		Oil		Gas	
	actual	forecast	actual	forecast	actual	forecast
Day 1	2.37	2.34	7.21	7.75	4.76	4.64
Day 2	2.39	2.37	7.26	7.20	4.85	4.74
Day 3	2.37	2.39	7.14	7.25	4.74	4.83
Day 4	2.39	2.37	7.21	7.14	4.74	4.72
Day 5	2.35	2.39	7.26	7.21	4.72	4.72
Day 6	2.39	2.35	7.16	7.25	4.65	4.70
Day 7	2.35	2.39	6.93	7.16	4.53	4.64

Table 7-6 Forecasted and actual prices in CM

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
Price ($/tonne)	4.03	3.90	3.98	3.98	3.90	3.90	3.93

In the real practice under a multimarket environment, a GENCO need to make decision based on limited information. For the short term planning which is the focus of this chapter, a GENCO can hardly affect the market clearing prices in the short term. The proposed model therefore considers the market prices as exogenous variables and make decision based on those forecast values. The forecasted data of the case study are given in Tables 7-3- 7-5, which are obtained using the methodology described in [24]. The markets date is assumed the same as that described in chapter 5. It is assumed that the feed-in-tariffs is fixed at 70USD/MWh, or else a GENCO can receive 16USD/MWh in addition to the revenue from EM when the fixed premium system is implemented. The historical wind speed dataset are obtained from a wind observation station in Tasmania, Australia. The data was provided by the Australian bureau of meteorology [185].

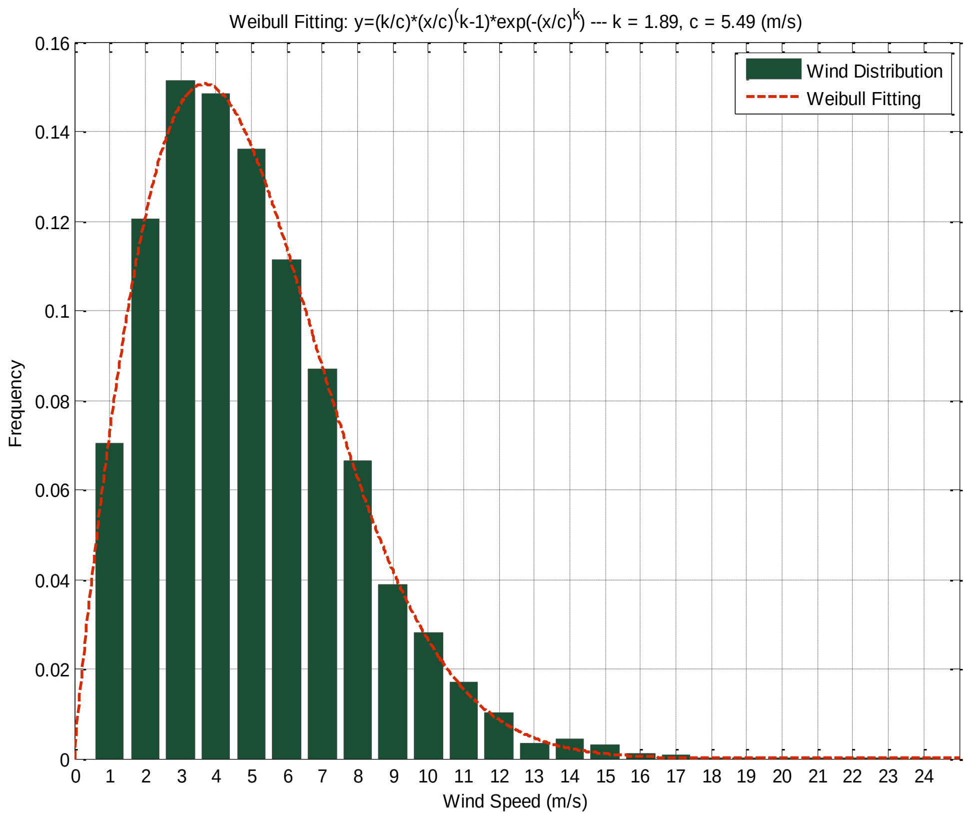

Fig. 7-6 Wind speed distribution and Weibull fitting

Fig.7-6 presents the Weibull distribution fitting of the wind speed data. The wind farm is assumed consisting totally of 30 Vestas V90 3.0 MW wind turbines [210] located in a coherent geographic area. The turbine is a pitch regulated upwind type with active yawing and a three-blade rotor. It has a rotor diameter of 90 m with a generator rated at 3.0 MW. The hourly average wind speed can be forecasted with the fitted Weibull distribution using the methodology described in [203]. The hourly wind energy outputs are then obtained according to (7-3). The characteristics of wind turbine and penalty cost coefficients are summarized in Table 7-7.

Table 7-7 Wind power parameters

c	k	θ	v_{in}	v_{out}	v_r	wr	$C_{u,j}$	$C_{o,j}$
5.49	1.89	0	4	25	16	3	5	30

Under a multimarket environment, there is little or no incremental cost associated with the wind power production. As the Feed-in-tariffs system can guarantee fixed revenue, a GENCO will plan to utilize all available wind output according to the forecast values. In the fix premium system, a GENCO decide the optimum wind energy output according to (7-10) and (7-11). The case might be different for the thermal units as they need to meet constraints not only from EM but also from FM and CM. The first stage of the decision making model for the GENCO is solved by FDE. FDE is different from the classical DE as the values of the searching parameters F and Cr are not fixed.

The convergence of FDE in the first planning hour in accordance with fuzzy control action can be observed from the characteristics shown in Figs. 7-7. The red, green, and blue lines represent the changes of the objective function, F, Cr values, respectively. The figure shows that the FDE algorithm needs a small number of generations (less than 100 times) to search the optimum value of the objective function. More details related to the advantages of FDE, which is out of the scope of this study, can be found in [209].With the FDE, the proposed model is solved to achieve the optimal volume of electricity output according to the interval forecasting of the energy output.

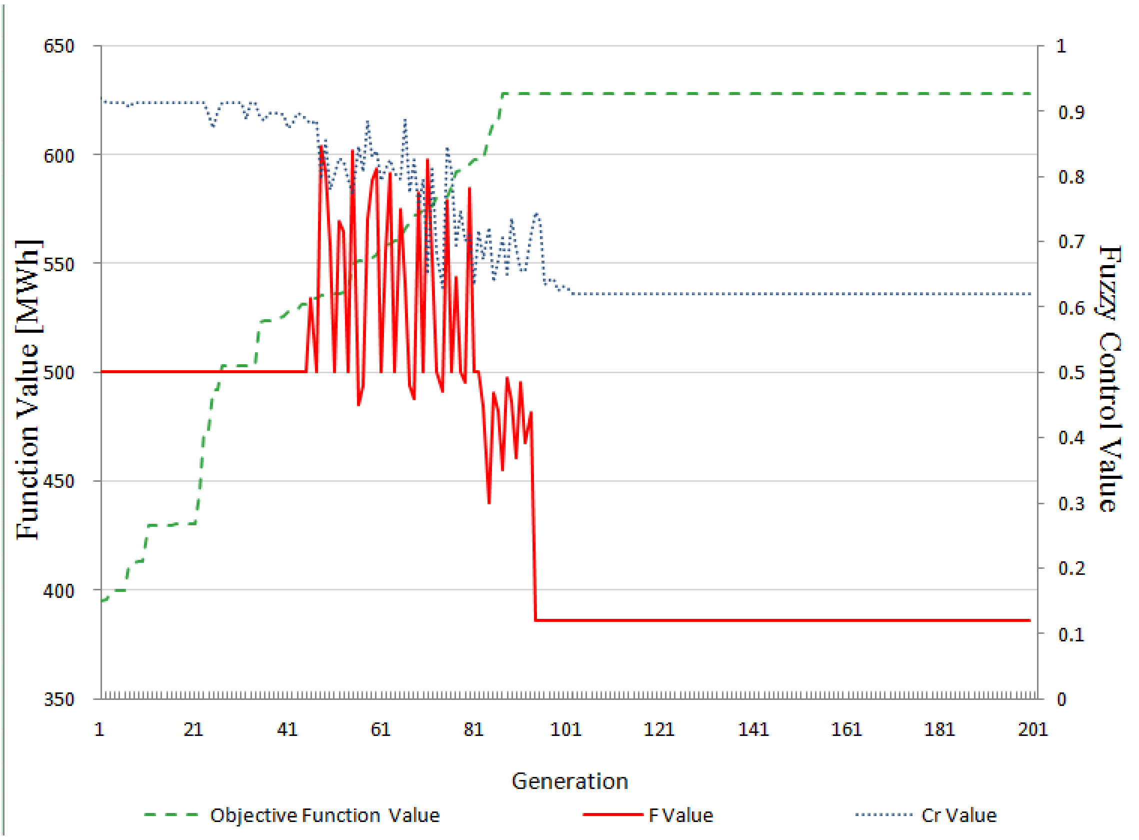

Fig. 7-7 Convergence of FDE in the first planning hour

In Fig.7-8 and Fig.7-9, the blue dotted line is the predicted upper bound of the energy output while the red solid line is the optimum hourly output that the GENCO decides to produce, which is composed of the planned output for the bilateral contract demand and the output for the power pool. The green solid line in Fig.7-8 represents the predicted wind power output, which is the scheduled wind power output of the GENCO under feed-in-tariffs. The counterpart under the fix premium system is represented by the grey line shown in Fig.7-9. The decision of stage 1 of the proposed model is made based on the forecasted market clearing price and constrains from the three interactive markets. Usually, the volume of the output for the power pool is determined with the bidding price simultaneously. However, a GENCO's bidding strategy is different from case to case and subjects to the clearing rules in the power market. Without loss of generalities, the case study would only analysis the output and the related trading profits. It can be observed from Fig.7-8 and Fig.7-9 that the GENCO decides to produce all forecasted energy by the wind farm under feed-in-tariffs while schedule the optimum volume of wind power under the fix premium system. Although the wind power has no incremental cost and contributes no emission, its uncertain nature leads to the least scheduling under the fix premium system at some time period. Because the revenue is not as fixed as in feed-in-tariffs system, the two penalties costs in (7-10) and (7-11) might result in negative revenue for a GENCO when electricity prices are relatively low at some hours. On the other hand, using more wind power enable a GENCO has superiority in CM as it can save more carbon allowances. At some hours with a relatively high electricity prices, the GENCO decides to schedule more wind power than the forecast values.

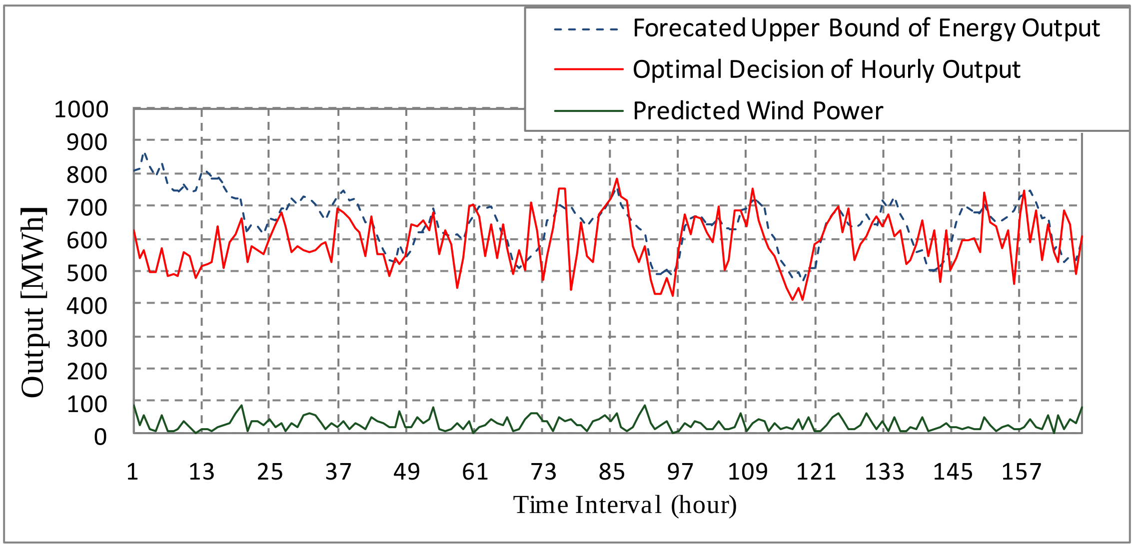

Fig. 7-8 Decision of hourly production under feed-in-tariffs

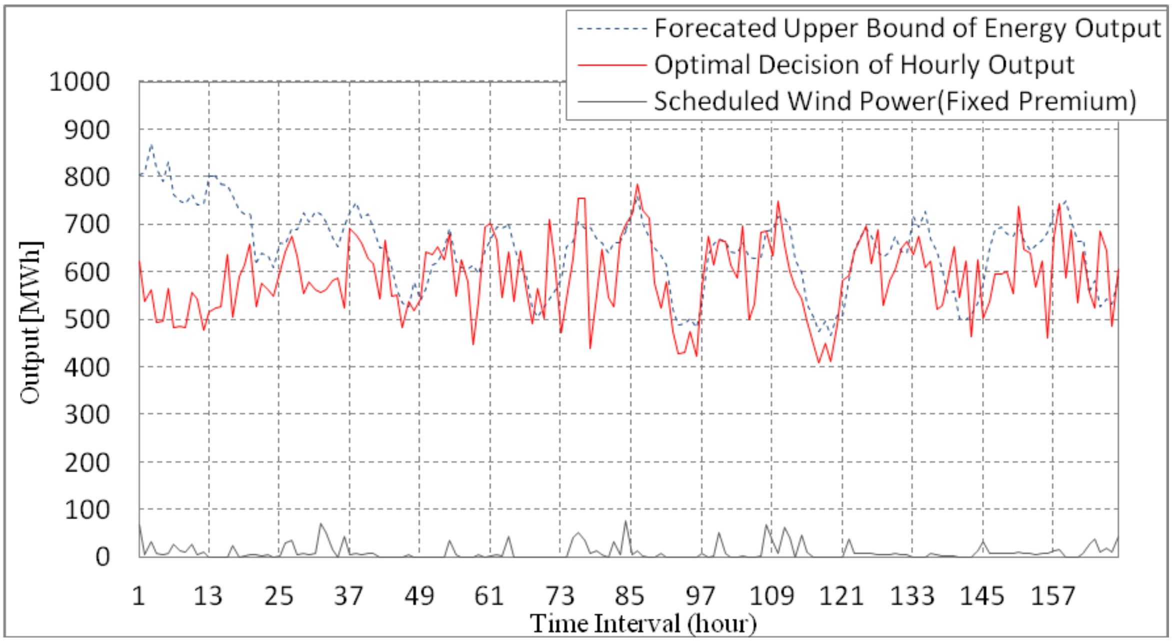

Fig. 7-9 Decision of hourly production under fix premium

Fig.7-10 and Fig.7-11 show the hourly production decisions of the seven units under the two RESS mechanisms. Unit 1 is a gas unit which is scheduled least among all the units as it has the highest fuel consumption function. On the contrary, unit 6 is a coal unit which provides the highest percentage of energy although it has the highest emission factor. It can be found that units 2 and 4 are dispatched as the last units during the GENCO's planning. In the study week, the wind farm (unit 7) contributes 4,831MWh energy production out of the total 83,008 MWh under the feed-in-tariffs system while the total volume is 1,867 MWh under the fix premium system. In terms of the GENCO's operation, it is reluctant to produce more than the thermal units' minimum outputs in some hours because of the relatively low prices in EM. The other reason for scheduling less wind power is because the forecast of wind power, which is related to the forecast of wind speed, is relatively low. Although the units are not scheduled freely due to the emission constraints, the proposed model can make a rational tradeoff between profit-making and emission reduction with the interactions among the three markets taken into account. From the viewpoint of EM operation, prices in the short term may increase if the majority of GENCOs decide to reduce their energy outputs. On the other hand, GENCOs might consider investing more in wind turbine units according to the price variations in CM and FM, and the subsidy in RM.

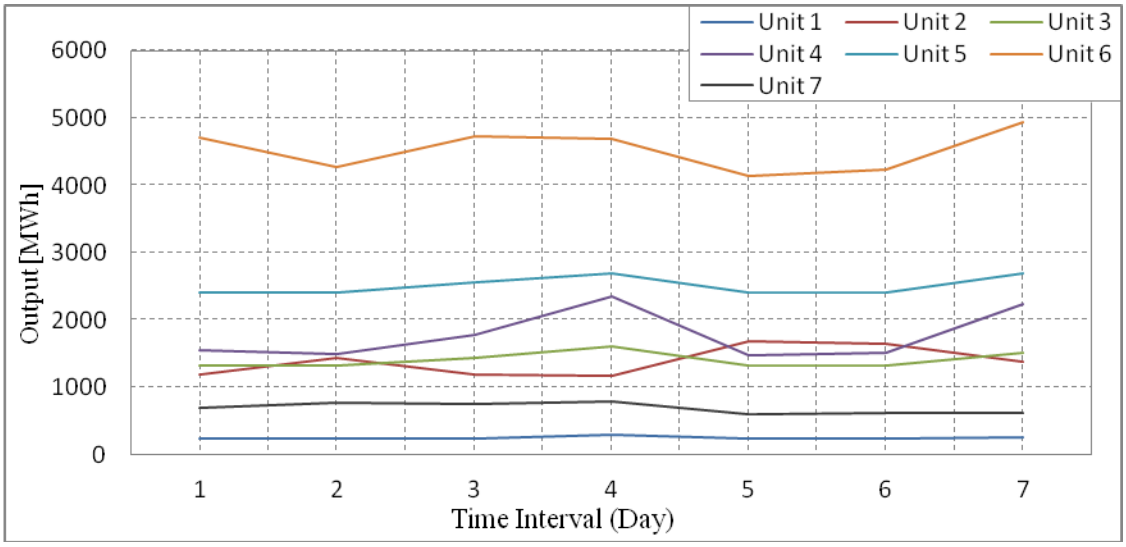

Fig. 7-10 Decision of daily production of the seven units under feed-in-tariffs

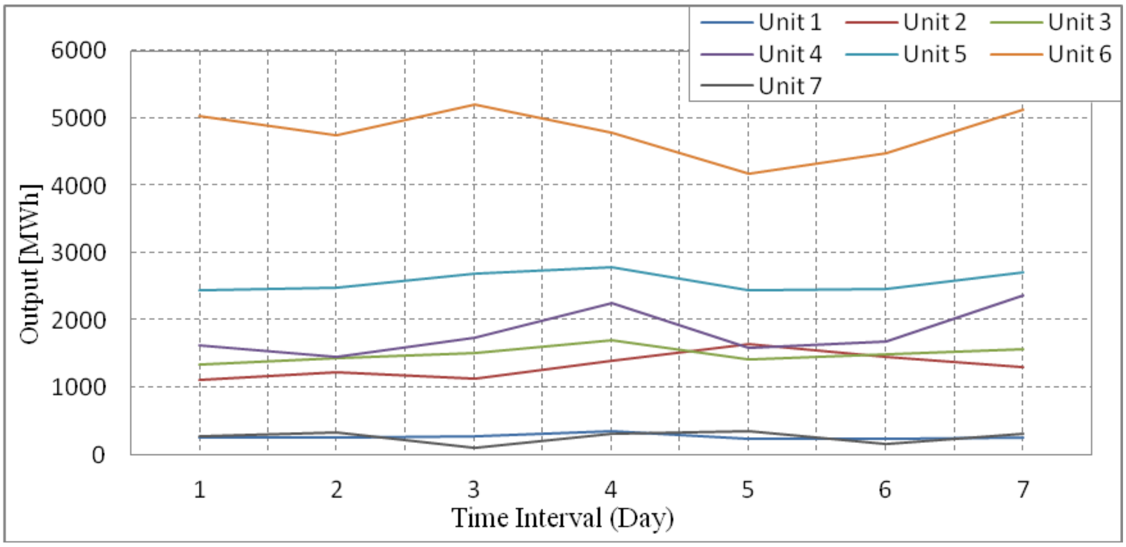

Fig. 7-11 Decision of daily production of the seven units under fix premium

Fig.7-12 and Fig.7-13 show the amount of daily emissions of the seven units using the two RESS method, respectively. The variations of daily emissions in the two scenarios are similar. Unit 7 is the wind farm, and therefore has no carbon emission at all. Units 1 and 6, corresponding to their energy productions, emit the least and the largest amounts of emission, respectively. Under the feed-in-tariffs system during the studied period, unit 2 produces 9,707MWh and unit 3 produces 9,853MWh. However, the total emission amount of unit 2 (34,119 tonne) is more than that of unit 3 (26,625 tonne). This is because the emission factor of unit 2 is higher than that of units 3 and 4. The emission distribution in the thermal units is similar but the emission increases due to the reduction of wind power using in the fix premium system.

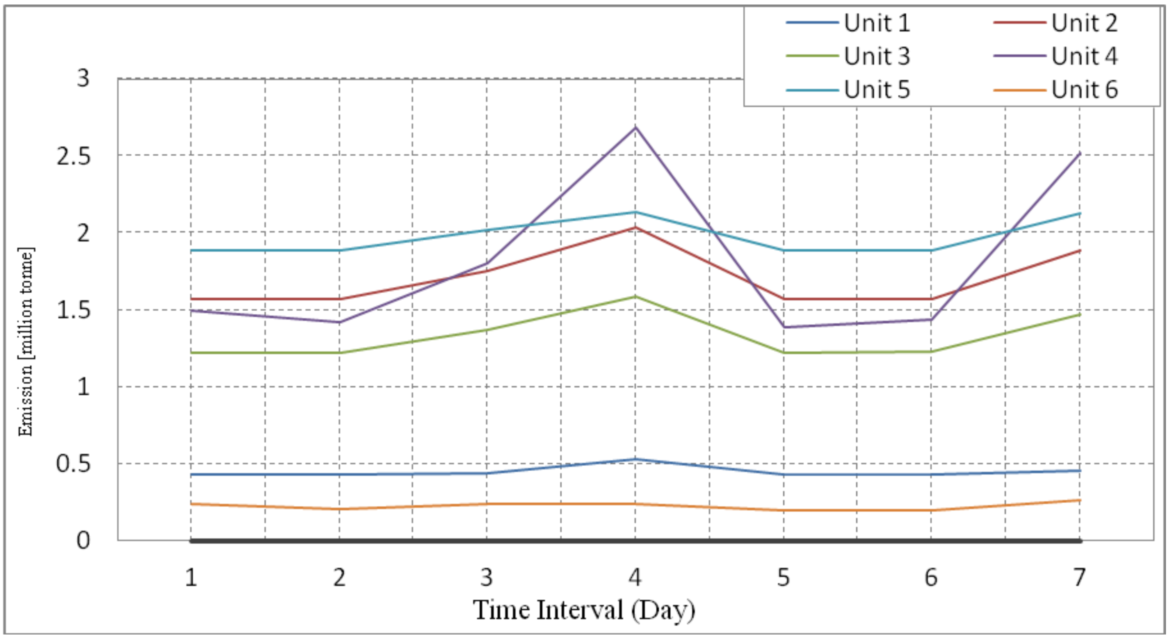

Fig. 7-12 Daily emissions of the 7 units under feed-in-tariffs

The largest difference of the produced emission in the two scenarios is the unit 6, with a 12% increase. Medium size units show their flexibility in the complex environment. Furthermore, with the CM, GENCO's emission is directly related to some fundamentals such as carbon prices, emission allowances, emission cap, penalty price and the mechanisms adopted in RM. A strict emission constraint and increasing percentage of renewable sources of course would lead to a lower carbon emission level. With a guarantee returns in the feed-in-tariffs system, a GENCO would reduce its thermal units output so as increase more wind energy output than that in the fix premium system. This would obviously lead to a larger total emission reduction in feed-in-tariffs system than that in the fix premium system.

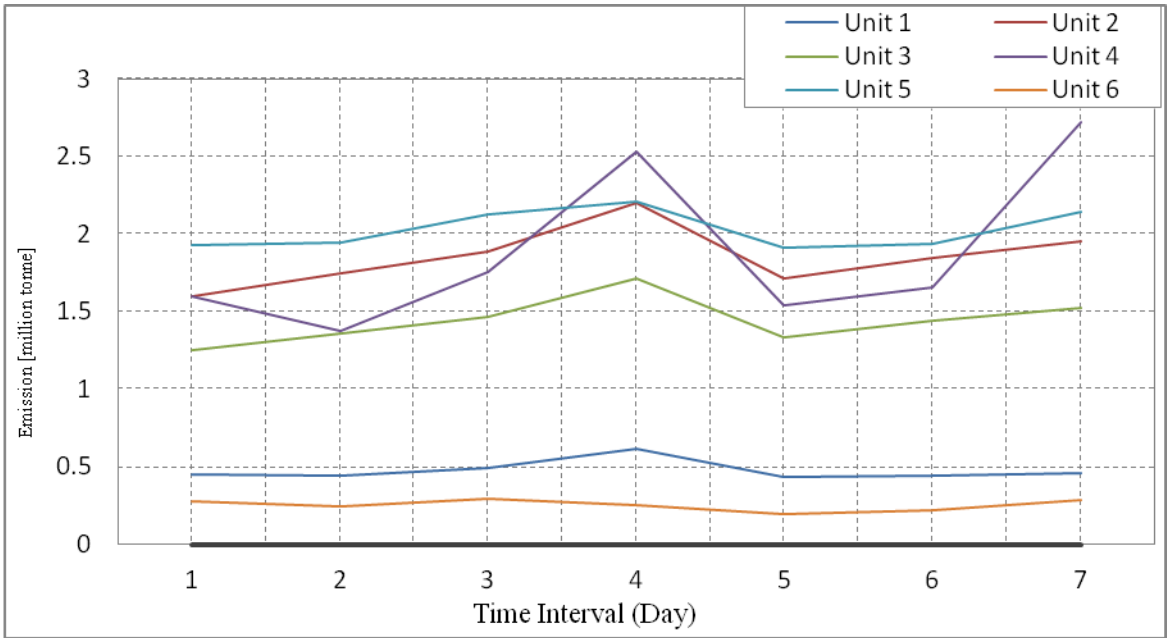

Fig. 7-13 Daily emissions of the 7 units under fix premium

Fig.7-14 and Fig.7-15 show the GENCO's daily revenues and total profits in the three interactive markets under feed-in-tariffs and fix premium, respectively. It can be observed that the revenue and profit profiles in the two scenarios are similar, expect the ones in EM and RM. Among all markets, the revenue from EM contributes most of the GENCO's profit in all the planning days. The revenue from EM under feed-in-tariffs is less than that under fix premium because the fixed feed-in-tariffs in RM would be paid for all power from the wind farm. On the contrary, the revenue from RM feed-in-tariffs is larger than that under fix premium. It is because a GENCO is paid not only the fixed premium in RM but also the electricity price in EM. On the whole, the GENCO's total revenue from EM and RM under fix premium is less than that under feed-in-tariffs.

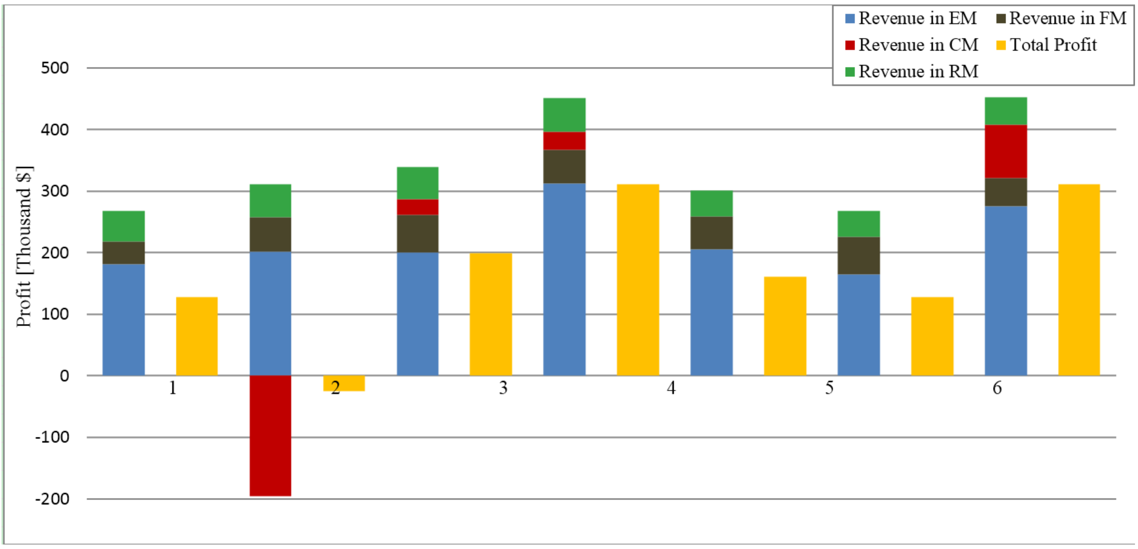

Fig. 7-14 Daily revenues and total profits of the GENCO under feed-in-tariffs

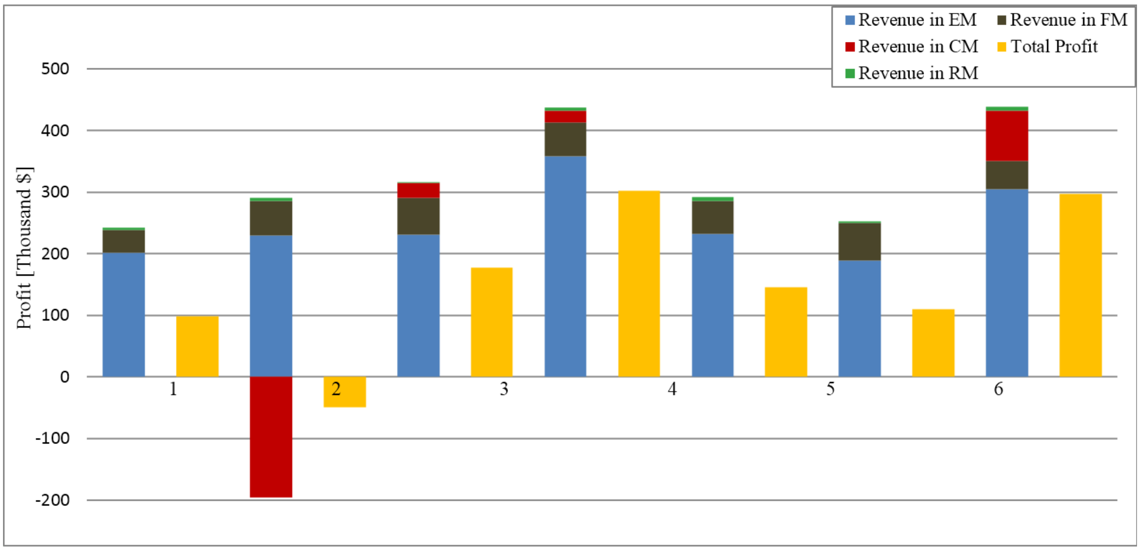

Fig. 7-15 Daily revenues and total profits of the GENCO units under fix premium

Using the proposed model, the decisions not only ensure the profits in EM and RM, but also seek for profits in other markets. As the study period is only one week, the trading behaviors in FM and CM are similar in the two scenarios. Due to the emission constraint, a GENCO would use all the available wind power. Besides, it has to reduce its energy production so as to limit the carbon pollution in the short run. These changes of the operation decision lead to some surplus of fuel from the long term fuel contracts which have been decided at the high level. At the low level, the GENCO would sell the surplus to seek for revenue from FM. Although the GENCO decides to sell some of the fuel in the FM most of the time, it buys a small amount of oil from FM according to (7-21). This is mainly because of the differences between the scheduling orders of unit productions. For instance, oil units 3 and 4 are chosen as the last units in some hours. Different from EM and FM, the trading in CM is subjected to more constraints. As the last day is the emission compliance day, the GENCO should at least balance the allowances with the produced emissions. It can be seen that the GENCO decides to purchase a certain amount of allowances in day 2 and sell them in days 3, 4, and 7 to make revenue from CM. On the whole, the implementation of environmental friendly policy like the CM would lead to a reduction of GENCO's profit. However, the decrease can be alleviated through the trading in the other markets under the multimarket environment.

Besides the profits and emissions in the planning period, it can be conjectured that ETS and RESS would together motivate the GENCO's assets planning (i.e., investing on renewables) at the high levels in the hierarchical decision making model. Subject to the demand fluctuation affected by ETS, prices in FM will be varied in the long run. Therefore GENCOs have to manage their fuel portfolio more efficiently. Furthermore, the implementation of carbon policies would immediately lead to a drop of profit for some GENCOs in the short term. Furthermore, the implementations of RESS in RM promote the GENCOs' usage of renewable energy e.g. wind power. It would benefit the GENCO's emission commitments in the CM. For the real practice in the long run, the impacts of CM are expected to become larger so that the trades in EM and CM can influence each other. Subject to the demand fluctuation affected by ETS, prices in FM will be varied in the long run. Therefore GENCOs have to manage their fuel portfolio more efficiently.

7.7. Summaries

For the purpose of analyzing the impacts of ETS on the decision making of a GENCO having wind power generation, a novel decision making model under an interactive multi-market environment was proposed. The model deals with the decision making problem by a two sequential stages. The first stage makes decisions in EM, RM and FM, and the second stage deals with trading in CM. The model accounts for emissions trading mechanisms by incorporating emissions constraints as well as the trading of emission allowances. A comprehensive case study is carried out to analyze the operation decisions of a GENCO subject to constraints of different markets. From the viewpoint of EM planning, a GENCO would preferably produce energy using more of its wind power according to the availability, and reduce part of its energy production from high emission units. Considering together with the impact of the two RESS mechanisms, a GENCO would consider investing in more renewable units with high priority in its production planning. The comparisons show that the feed-in-tariffs system leads to more emission reduction than in the fix premium system. With a certain revue in RM in the feed-in-tariffs, a GENCO dare to use more wind power according to the forecast values. Whilst the GENCO has to decide the optimum wind output in the fix premium system subject to the volatile electricity prices. From CM's viewpoint, a GENCO tends to make a reasonable tradeoff between reducing its emission and purchasing allowances by using the proposed model. The fluctuation of the prices is an incentive for a GENCO to seek for profits in CM. The GENCO which owns wind farms has advantages to earn more in CM so that it tends to stimulate the power industry to increase the penetration of wind power. From the standpoint of FM, the fuels cost affects the incremental cost of the thermal units significantly. The proposed model can help GENCOs to fully utilize the contracted fuels and decide the trading in the spot market. A GENCO will change its fuel portfolio dynamically with consideration of the price fluctuations in EM, FM and CM.

Although this study includes the FM externalities, embodied in fuel price variations, it does not take fuel portfolio formulation into account. It is an essential problem for a GENCO as it has to consider cost variations of fuel, transportation, storage and other services, which can be included in our further study.

CHAPTER 8. CONCLUSION

8.1. Contributions of This Research

The focus of this thesis is to develop advanced intelligent based methods to enable environmental and economical analysis in electricity market planning and management. This thesis addresses several important technical and economic issues associated with two major challenging parts in the deregulated electricity market; which are, 1) gaining insightful knowledge of price schemes in deregulated electricity markets and 2) studying the impacts of emission trading on the electricity markets planning and operation. The main contributions of this thesis are summarized below:

In Chapter 2, a comprehensive review on the two main parts is provided, as well as existing techniques relevant to these two difficult problems. The available pricing mechanisms for both real power and reactive power are categorized in the first part. The second part contributes to identify the role of ETS in the electricity supply industry worldwide and investigate its impact on the four interactive markets' operations. This is a comprehensive review to analyze on the interaction among electricity market, fuel market, carbon market and renewable market through the role of ETS. The analysis of the impacts of ETS on different markets revolving around the electricity supply industry has been conducted. This chapter covers analysis on electricity market, carbon market, fuel market, and renewable market.

Based on the observations from literature review, the objectives of this thesis is determined to meet the above two major challenge parts in the deregulated electricity market. The objectives of research are well achieved, with a number of major contributions listed below:

In Chapter 3, a two-stage hybrid method based on panel cointegration and particle filter (PCPF) that can accurately forecast electricity prices is developed. Panel cointegration (PC) model provides a kind of powerful forecasting tool, which utilizes information of both the inter-temporal dynamics and the individuality of interconnected regions. Particle filter (PF) has achieved significant success in tracking applications involving non-Gaussian signals and nonlinear systems. Making use of the advantages of both techniques, this hybrid method has two main focuses: 1) To expand the dimension of electricity price dataset from time series to panel data so that the dynamics of interconnected regions can be analyzed simultaneously and considered as a whole. 2) Regarding the model coefficient as a time-varying process, PF is used to forecast electricity price adaptively. This chapter covers analysis on electricity market and focus on the real power pricing mechanism.

In Chapter 4, a novel value based reactive power procurement scheme in electricity markets is developed to quantify the price of the reactive power source output. Analyzing the cost of providing reactive power service and establishing appropriate pricing structure are important both financially and operationally for reactive power procurement. This study presents an advanced model for procuring reactive power from reactive resources based on a reactive power pricing structure. The model takes into account reactive power capacity and production cost as well as the value of reactive power. This chapter covers analysis on electricity market and focus on the pricing mechanism of the reactive power.

Based on the outcomes of the first part, the second part studies the impacts of emission trading on the operation of electricity markets, including the consideration of multimarket environment, renewable energy support schemes and wind power uncertainty:

In Chapter 5, a novel dynamic decision making model is proposed to deal with the multimarket trading problem for a GENCO in each trading period. Differential evolution (DE) is employed to solve the multi-period stochastic optimization problem and give the optimum results for each time interval. With the proposed model, a GENCO can make a good trade-off between profit-making and emission reduction under the three interactive markets environment. This chapter investigates the impacts of carbon policies on a GENCO's decision making under multimarket environment. This chapter covers analysis on electricity market, carbon market, and fuel market.

In Chapter 6, a novel agent-based market simulation model accounts for both emission trading and renewable energy support schemes. This study employs replicator dynamics algorithm, which is employed to simulate the bidding strategies of agents (generation companies) for profit maximization. The operation process of an electricity market is simulated over a studied time horizon and some indices are employed to evaluate the market operation performance. Impacts of emission trading and renewable energy support schemes on electricity market operation are investigated through the electricity market planning. This chapter covers analysis on electricity market, carbon market, and renewable market.

In Chapter 7, a novel dynamic decision making model is proposed to investigate GENCO's decision making considering wind power uncertainty and emission trading under multimarket environment. Besides ETS, the effects of RESS (fixed feed-in tariffs and the fixed premium) on GENCO's operation in the interactive markets are analyzed. Particularly, wind power, being one of the most appealing renewable energy resources, has gained widespread concerns during the last decade. A novel probability method based on non-linear wind power curve and Weibull distribution is developed to identify the role of wind power. Comparisons among different scenarios demonstrate the economic and environmental influences of different policies on a GENCO. This chapter covers analysis on electricity market, carbon market, fuel market and renewable market.

8.2. Directions for Future Research

Following the research route depicted in Fig.1-1, the objectives of this research have been successfully achieved. Based on a number of achievements made in this research, several directions for further research are suggested below:

A. Based on the real price forecasting technique described in chapter 3, chapters 5, 6 and 7 have proposed several effective models which would benefit electricity market operation under multimarket environments. One of the future attentions will therefore be paid on investigating how to quantify the price of reactive power source output with consideration of wind power uncertainty so that it is able to procure reactive support competitively under the multi-market environment. Following the future research route, I will plan to investigate how to quantify the price of the reactive power source output when considering wind power uncertainty based on the findings in chapter 4. In this manner, it is able to procure reactive support competitively under the multi-market environment in the future work. This is of importance for power system planning and operation with the increasing penetration of renewable like wind power.

B. Although this thesis includes FM externalities, embodied in fuel price variations in chapter 5 and chapter 7, the fuel portfolio formulation is not taken into account in order to reduce the complexity of the model. However, this is an essential problem for a GENCO as it has to consider cost variations of fuel, transportation, storage and other services in FM. As fuel cost is still the major factor affecting GENCOs' decision making, a GENCO will change its fuel portfolio dynamically with consideration of the price fluctuations in EM, FM, RM and CM. This is of importance for the electricity market planning and operation with the increasing penetration of renewable such as wind power.

C. With the development of smart grid, more and more attentions have been paid to the plug-in hybrid electric vehicle (PHEV) and vehicle-to-grid (V2G) technologies. On one hand, large number of PHEVs charge simultaneously would impact demand peaks, reduce reserve margins, and increase prices. On the other hand, the battery in PHEVs can be used as energy storage to mitigate the fluctuations of renewable energy. There are more than 90% of personal vehicles are not in used for transportation even in traffic peak period, making them potentially available to the grid. Under a multimarket environment, the utilization of the V2G charger system for both the real power and the reactive power support to the grid will be prospected in the future work. From the aspect of real power, V2G can provide competitive price when supplying peak power, spinning reserves and regulation. From the aspect of reactive power management, PHEV can provide spinning reserves and regulation due to its fast response ability. They are ideally suited to meet the grid stability and reliability challenges as providers of grid support, or ancillary services. For instance, PHEV are able to provide both regulation up and regulation down in frequency regulation. Furthermore, PHEV fleet can also be treated as controllable load or even generator to charge on valley period and discharge on peak period.

D. Based on the research described in chapter 6 and chapter 7, the impacts of emission trading and RESS on electricity market operation have been investigated in details. In these two chapters particularly attentions have been paid to the two most important RESSs, namely the fixed feed-in tariffs and the fixed premium. However, nowadays there is an increasing trend to adopt the other category of RESSs, namely fix-quantity systems, in the development in RM. Fix-quantity systems has two variations: renewable portfolio standard (RPS) and tradable green certificates. RPS requires electricity generation entities to produce or purchase a certain percentage of their electricity from renewable energy sources by a specified date. RPS regulates the quantity on the generation side while tradable green certificates apply on the consumer side. Tradable green certificates require retailers to purchase a certain amount of certificates. They are subject to a penalty for any shortfall of the pre-determined amount. Since the fix-quantity systems and ETS usually coexist and both have the overlapping goal of reducing CO_2 emissions, they interact in complex ways, mainly through their respective effects on key electricity market variables (i.e. prices). These interactions, which may lead to conflicts and/or synergies, are needed to be analyzed because one policy may have positive or negative effects on the other.

8.3. Summary

This chapter concludes the thesis and highlights the contributions and main achievements of the researches during the study. It also identifies several directions for future work involving the approaches developed in the thesis. Overall, the research work done here provides a comprehensive framework for environmental and economical analysis in electricity market which enhances the operation and market trading of power system, as well as the planning functionality of its operators.

REFERENCES

[1] E. Vine, J. Hamrin, N. Eyre, D. Crossley, M. Maloney, G. Watt, Public policy analysis of energy efficiency and load management in changing electricity businesses, Energy Policy, 31 (2003) 405-430.

[2] K. Protocol, United Nations framework convention on climate change, Kyoto Protocol, Kyoto, (1997).

[3] A.D. Ellerman, I.S. Wing, Absolute versus intensity-based emission caps, Climate Policy, 3 (2003) S7-S20.

[4] H. Park, J.W. Mjelde, D.A. Bessler, Price interactions and discovery among natural gas spot markets in North America, Energy Policy, 36 (2008) 290-302.

[5] F. Asche, P. Osmundsen, M. Sandsmark, The UK market for natural gas, oil and electricity: are the prices decoupled?, The Energy Journal, 27 (2006) 27-40.

[6] Hassan Mohammadi, Electricity prices and fuel costs: Long-run relations and short-run dynamics, Energy Economics, 31 (2009), 503-509.

[7] S. Takriti, B. Krasenbrink, L.S.Y. Wu, Incorporating fuel constraints and electricity spot prices into the stochastic unit commitment problem, Operations Research, 48 (2000) 268-280.

[8] J.W. Mjelde, D.A. Bessler, Market integration among electricity markets and their major fuel source markets, Energy Economics, 31 (2009) 482-491.

[9] M. Babiker, J.M. Reilly, H.D. Jacoby, The Kyoto Protocol and developing countries, Energy Policy, 28 (2000) 525-536.

[10] V.H. Hoffmann, EU ETS and Investment Decisions: The Case of the German Electricity Industry, European Management Journal, 25 (2007) 464-474.

[11] E.C. Exchange., Emissions Prices Drop to 13-Month Low After Sweden Shows Surplus 2006a, 2006.

[12] K. Capoor, P. Ambrosi, State and trends of the carbon market 2006, World Bank Carbon Finance Unit, 2006.

[13] Y. Chen, Does a regional greenhouse gas policy make sense? A case study of carbon leakage and emissions spillover, Energy Economics, 31 (2009) 667-675.

[14] I. MacGill, H. Outhred, K. Nolles, Some design lessons from market-based greenhouse gas regulation in the restructured Australian electricity industry, Energy Policy, 34 (2006) 11-25.

[15] C. Zhang, P. Shukla, D.G. Victor, T.C. Heller, D. Biswas, T. Nag, Baselines for carbon emissions in the Indian and Chinese power sectors: Implications for international carbon trading, Energy Policy, 34 (2006) 1900-1917.

[16] A. Kossoy, P. Ambrosi, State and trends of the carbon market, Washington, DC: The World Bank, (2010).

[17] A. Ford, P.S. Fereidoon, Global Climate Change and the Electric Power Industry, in: Competitive Electricity Markets, Elsevier, Oxford (2007) 499-542.

[18] T. Tsoutsos, E. Papadopoulou, A. Katsiri, A.M. Papadopoulos, Supporting schemes for renewable energy sources and their impact on reducing the emissions of greenhouse gases in Greece, Renewable and Sustainable Energy Reviews, 12 (2008) 1767-1788.

[19] E. Maria, T. Tsoutsos, The sustainable management of renewable energy sources installations: legal aspects of their environmental impact in small Greek islands, Energy Conversion and Management, 45 (2004) 631-638.

[20] G.Z. Liu, C.W. Yu, X.R. Li, F.S. Wen, Impacts of emission trading and renewable energy support schemes on electricity market operation, IET Generation, Transmission & Distribution , 5 (2011) 650-655.
[21] A. Singh, A market for renewable energy credits in the Indian power sector, Renewable and Sustainable Energy Reviews, 13 (2009) 643-652.
[22] X.R. Li, C.W. Yu, Interaction analysis among Electricity Market, Carbon Market And Renewable Market: A review of emission trading, in: Advances in Power System Control, Operation and Management (APSCOM 2009), 2009, pp. 1-8.
[23] M. Alonso, H. Amaris, C. Alvarez-Ortega, Integration of renewable energy sources in smart grids by means of evolutionary optimization algorithms, Expert Systems with Applications, 39 (2012) 5513-5522.
[24] X.R. Li, C.W. Yu, S. Ren, K. Meng, G. Liu, Day-ahead electricity market price forecasting based on Panel Cointegration, in: Power and Energy Society General Meeting, 2010, pp. 1-7.
[25] X. Li, C. Yu, S. Ren, C. Chiu, K. Meng, Day-ahead electricity price forecasting based on panel cointegration and particle filter, Electric Power Systems Research, 95 (2013) 66-76.
[26] X.J. Lin, C.W. Yu, A.K. David, C.Y. Chung, H. Wu, N. Xu, A novel market-based reactive power management scheme, International Journal of Electrical Power & Energy Systems, 28 (2006) 127-132.
[27] X. Li, C. Yu, W. Chen, A novel value based reactive power procurement scheme in electricity markets, International Journal of Electrical Power & Energy Systems, 43 (2012) 910-914.
[28] S. Han, K. Sezaki, Development of an optimal vehicle-to-grid aggregator for frequency regulation, IEEE Transactions on Smart Grid, 1 (2010) 65-72.
[29] X.R. Li, C.W. Yu, F.J. Luo, S.Y. Ren, Z.Y. Dong, K.P. Wong, Impacts of emission trading schemes on GENCOs' decision making under multimarket environment, Electric Power Systems Research, 95 (2013) 257-267.
[30] N.M. Pindoriya, S.N. Singh, S.K. Singh, An adaptive wavelet neural network-based energy price forecasting in electricity markets, IEEE Transactions on Power Systems, 23 (2008) 1423-1432.
[31] C.W. Yu, X.S. Zhao, F.S. Wen, C.Y. Chung, T.S. Chung, M.X. Huang, Pricing and procurement of operating reserves in competitive pool-based electricity markets, Electric Power Systems Research, 73 (2005) 37-43.
[32] M. Benini, M. Marracci, P. Pelacchi, A. Venturini, Day-ahead market price volatility analysis in deregulated electricity markets, in: Power Engineering Society Summer Meeting, 2002, pp. 1354-1359.
[33] R. Jammazi, C. Aloui, Crude oil price forecasting: Experimental evidence from wavelet decomposition and neural network modeling, Energy Economics, 34 (2012) 828-841.
[34] J.H. Zhao, Z.Y. Dong, Z. Xu, K.P. Wong, A statistical approach for interval forecasting of the electricity price, IEEE Transactions on Power Systems, 23 (2008) 267-276.
[35] P. Asare, A. Galli, J. Lee, C. Lozano, E. O'Neill-Carillo, R. Zhao, Real Time Pricing of Electric Power, (1995).
[36] C.M. Ruibal, M. Mazumdar, Forecasting the Mean and the Variance of Electricity Prices in Deregulated Markets, IEEE Transactions on Power Systems , 23 (2008) 25-32.

[37] B. Zerlentes, G.J.D. Hewings, S. Weiler, Modeling production externalities in the maquila industry, Ecological Economics, 68 (2009) 822-835.
[38] R.C. Garcia, J. Contreras, M. Van Akkeren, J.B.C. Garcia, A GARCH forecasting model to predict day-ahead electricity prices, IEEE Transactions on Power Systems, 20 (2005) 867-874.
[39] K. Meng, Z. Dong, K. Wong, Self-adaptive radial basis function neural network for short term electricity price forecasting, IET Generation, Transmission & Distribution, 3 (2009) 325-335.
[40] G. Li, C.C. Liu, C. Mattson, J. Lawarrée, Day-ahead electricity price forecasting in a grid environment, IEEE Transactions on Power Systems, 22 (2007) 266-274.
[41] L. Wu, M. Shahidehpour, A hybrid model for day-ahead price forecasting, IEEE Transactions on Power Systems, 25 (2010) 1519-1530.
[42] N. Amjady, Day-ahead price forecasting of electricity markets by a new fuzzy neural network, IEEE Transactions on Power Systems, 21 (2006) 887-896.
[43] D.W. Bunn, C.J. Day, Computational modelling of price formation in the electricity pool of England and Wales, Journal of Economic Dynamics and Control, 33 (2009) 363-376.
[44] U.F.E.R. Commission, Promoting wholesale competition through open access non-discriminatory transmission services by public utilities; recovery of stranded costs by public utilities and transmitting utilities, Order, 888 (1996) 24.
[45] P. Frías, T. Gómez, D. Soler, A reactive power capacity market using annual auctions, IEEE Transactions on Power Systems, 23 (2008) 1458-1468.
[46] I. El-Samahy, K. Bhattacharya, C. Caizares, M.F. Anjos, J. Pan, A procurement market model for reactive power services considering system security, IEEE Transactions on Power Systems, 23 (2008) 137-149.
[47] P.R. Gribik, D. Shirmohammadi, S. Hao, C.L. Thomas, Optimal power flow sensitivity analysis, IEEE Transactions on Power Systems, 5 (1990) 969-976.
[48] N. Dandachi, M. Rawlins, O. Alsac, M. Prais, B. Stott, OPF for reactive pricing studies on the NGC system, IEEE Transactions on Power Systems, 11 (1996) 226-232.
[49] W. Xu, Y. Zhang, L.C.P. da Silva, P. Kundur, A.A. Warrack, Valuation of dynamic reactive power support services for transmission access, IEEE Transactions on Power Systems, 16 (2001) 719-728.
[50] M.L. Baughman, S.N. Siddiqi, J.W. Zarnikau, Advanced pricing in electrical systems. II. Implications, IEEE Transactions on Power Systems, 12 (1997) 496-502.
[51] J.W. Lamont, J. Fu, Cost analysis of reactive power support, IEEE Transactions on Power Systems, 14 (1999) 890-898.
[52] Y. Dai, Y. Ni, C. Shen, F. Wen, Z. Han, F.F. Wu, A study of reactive power marginal price in electricity market, Electric Power Systems Research, 57 (2001) 41-48.
[53] M.M. Araújo, O.R. Saavedra, R.B. Prada, Allocation of reactive power support based on a voltage source model, International Journal of Electrical Power & Energy Systems, 33 (2011) 439-444.
[54] J. Bialek, Topological generation and load distribution factors for supplement charge allocation in transmission open access, IEEE Transactions on Power Systems, 12 (1997) 1185-1193.

[55] F.F. Wu, Y. Ni, P. Wei, Power transfer allocation for open access using graph theory-fundamentals and applications in systems without loopflow, IEEE Transactions on Power Systems, 15 (2000) 923-929.
[56] A. Khazali, M. Kalantar, Optimal reactive power dispatch based on harmony search algorithm, International Journal of Electrical Power & Energy Systems, (2011).
[57] W.C. Chu, B.K. Chen, C.H. Liao, Allocating the costs of reactive power purchased in an ancillary service market by modified Y-bus matrix method, IEEE Transactions on Power Systems, 19 (2004) 174-179.
[58] X.J. Lin, C.W. Yu, C.Y. Chung, Pricing of reactive support ancillary services, IET Generation, Transmission & Distribution, 152 (2005) 616-622.
[59] A. Ketabi, A. Alibabaee, R. Feuillet, Application of the ant colony search algorithm to reactive power pricing in an open electricity market, International Journal of Electrical Power & Energy Systems, 32 (2010) 622-628.
[60] R.H. Coase, The Problem of Social Cost, Journal of Law and Economics 3(1960) 44.
[61] C.H. Li, Y. Cheng, L.Z. Zhang, Research of Environment Externalities Control of Power Plants in Electricity Market, in: Joint International Conference on Power Systems Technology (POWERCON)/IEEE Power Conference, New Delhi, INDIA, 2008, pp. 415-421.
[62] B. Hansjürgens, Emissions Trading for Climate Policy: US and European Perspectives, Cambridge University Press, (2005).
[63] G.W. Yohe, D. Montgomery, E. Balistreri, Equity and the Kyoto Protocol: measuring the distributional effects of alternative emissions trading regimes, Global Environmental Change, 10 (2000) 121-132.
[64] K. Rypdal, W. Winiwarter, Uncertainties in greenhouse gas emission inventories -- evaluation, comparability and implications, Environmental Science & Policy, 4 (2001) 107-116.
[65] C. Boemare, P. Quirion, Implementing greenhouse gas trading in Europe: lessons from economic literature and international experiences, Ecological Economics, 43 (2002) 213-230.
[66] W. Chen, Carbon quota price and CDM potentials after Marrakesh, Energy Policy, 31 (2003) 709-719.
[67] H. Laurikka, U. Springer, Risk and return of project-based climate change mitigation: a portfolio approach, Global Environmental Change, 13 (2003) 207-217.
[68] U. Springer, International diversification of investments in climate change mitigation, Ecological Economics, 46 (2003) 181-193.
[69] Y. Hu, C.R. Monroy, Chinese energy and climate policies after Durban: Save the Kyoto Protocol, Renewable and Sustainable Energy Reviews, 16 (2012) 3243-3250.
[70] Wiley, Fundamentals of Power System Economics in: G.S. Daniel S. Kirschen (Ed.), 2004
[71] P.M. Bernstein, W.D. Montgomery, S.D. Tuladhar, Potential for reducing carbon emissions from non-Annex B countries through changes in technology, Energy Economics, 28 (2006) 742-762.
[72] H. Laurikka, T. Koljonen, Emissions trading and investment decisions in the power sector - A case study in Finland, Energy Policy, 34 (2006) 1063-1074.

[73] N. Linacre, A. Kossoy, P. Ambrosi, State and trends of the carbon market 2012, Washington DC: World Bank, (2012).
[74] B. Mizrach, Integration of the global carbon markets, Energy Economics, 34 (2012) 335-349.
[75] I. Rampidis, D. Giannakopoulos, G. Bergeles, Insight into the Greek electric sector and energy planning with mature technologies and fuel diversification, Energy Policy, 38 (2010) 4076-4088.
[76] D. Porter, S. Rassenti, W. Shobe, V. Smith, A. Winn, The design, testing and implementation of Virginia's NOx allowance auction, Journal of Economic Behavior & Organization, 69 (2009) 190-200.
[77] L.H. Goulder, M.A.C. Hafstead, M. Dworsky, Impacts of alternative emissions allowance allocation methods under a federal cap-and-trade program, Journal of Environmental Economics and Management, 60 (2010) 161-181.
[78] R.G. Cong, Y.M. Wei, Potential impact of (CET) carbon emissions trading on China's power sector: A perspective from different allowance allocation options, Energy, 35 (2010) 3921-3931.
[79] F. Convery, D. Ellerman, C. De Perthuis, The European carbon market in action: Lessons from the first trading period, Journal for European Environmental & Planning Law, 5 (2008) 215-233.
[80] C. Böhringer, K.E. Rosendahl, Strategic partitioning of emission allowances under the EU Emission Trading Scheme, Resource and Energy Economics, 31 (2009) 182-197.
[81] M. Jaccard, W.D. Montgomery, Costs of reducing greenhouse gas emissions in the USA and Canada, Energy Policy, 24 (1996) 889-898.
[82] E. Tjernström, T. Tietenberg, Do differences in attitudes explain differences in national climate change policies?, Ecological Economics, 65 (2008) 315-324.
[83] T. Tietenberg, Ethical influences on the evolution of the US tradable permit approach to air pollution control, Ecological Economics, 24 (1998) 241-257.
[84] S. Shaw, E. Peteves, Exploiting synergies in European wind and hydrogen sectors: A cost-benefit assessment, International Journal of Hydrogen Energy, 33 (2008) 3249-3263.
[85] A. Menegaki, Valuation for renewable energy: A comparative review, Renewable and Sustainable Energy Reviews, 12 (2008) 2422-2437.
[86] A. Stirling, Limits to the value of external costs, Energy Policy, 25 (1997) 517-540.
[87] A. Stirling, Diversity and ignorance in electricity supply investment : Addressing the solution rather than the problem, Energy Policy, 22 (1994) 195-216.
[88] R.W. Hahn, The Impact of Economics on Environmental Policy, Journal of Environmental Economics and Management, 39 (2000) 375-399.
[89] R.W. Hahn, Regulatory constraints on environmental markets, Journal of Public Economics, 42 (1990) 149-175.
[90] A.B. Jaffe, R.G. Newell, R.N. Stavins, A tale of two market failures: Technology and environmental policy, Ecological Economics, 54 (2005) 164-174.
[91] L. Mundaca, Markets for energy efficiency: Exploring the implications of an EU-wide 'Tradable White Certificate' scheme, Energy Economics, 30 (2008) 3016-3043.
[92] L. Chernyavs'ka, F. Gull, Marginal CO_2 cost pass-through under imperfect competition in power markets, Ecological Economics, 68 (2008) 408-421.

[93] B.D. Solomon, New directions in emissions trading: the potential contribution of new institutional economics, Ecological Economics, 30 (1999) 371-387.
[94] N.R. Netusil, J.B. Braden, Transaction costs and sequential bargaining in transferable discharge permit markets, Journal of Environmental Management, 61 (2001) 253-262.
[95] O. Rousse, Environmental and economic benefits resulting from citizens' participation in CO2 emissions trading: An efficient alternative solution to the voluntary compensation of CO2 emissions, Energy Policy, 36 (2008) 388-397.
[96] R. B. Howarth, B.M. Haddad, B. Paton, The economics of energy efficiency: insights from voluntary participation programs, Energy Policy, 28 (2000) 477-486.
[97] L.A. Bird, E. Holt, G. Levenstein Carroll, Implications of carbon cap-and-trade for US voluntary renewable energy markets, Energy Policy, 36 (2008) 2063-2073.
[98] A. Mendoza Beltran, M.G.J. den Elzen, A.F. Hof, D.P. van Vuuren, J. van Vliet, Exploring the bargaining space within international climate negotiations based on political, economic and environmental considerations, Energy Policy, 39 (2011) 7361-7371.
[99] J. Pearlman, T. Baumann, International Greenhouse Gas Standards To Support Sustainable Global Energy, in: IEEE Energy 2030 Conference, 2008, pp. 1-4.
[100] A. Bernard, A. Haurie, M. Vielle, L. Viguier, A two-level dynamic game of carbon emission trading between Russia, China, and Annex B countries, Journal of Economic Dynamics and Control, 32 (2008) 1830-1856.
[101] L. Szab, I. Hidalgo, J.C. Ciscar, A. Soria, CO_2 emission trading within the European Union and Annex B countries: the cement industry case, Energy Policy, 34 (2006) 72-87.
[102] M.G.J. den Elzen, A.P.G. de Moor, Analyzing the Kyoto Protocol under the Marrakesh Accords: economic efficiency and environmental effectiveness, Ecological Economics, 43 (2002) 141-158.
[103] A. Farrell, Multi-lateral emission trading: lessons from inter-state NOx control in the United States, Energy Policy, 29 (2001) 1061-1072.
[104] L.C. Sieghart, Unilateral Clean Development Mechanism - An approach for a least developed country?: The case of Yemen, Environmental Science & Policy, In Press, Corrected Proof (2009).
[105] A.S. Malik, Further Results on Permit Markets with Market Power and Cheating, Journal of Environmental Economics and Management, 44 (2002) 371-390.
[106] A.S. Malik, Markets for pollution control when firms are noncompliant, Journal of Environmental Economics and Management, 18 (1990) 97-106.
[107] A.D. Yucekaya, J. Valenzuela, G. Dozier, Strategic bidding in electricity markets using particle swarm optimization, Electric Power Systems Research, 79 (2009) 335-345.
[108] J. Doege, M. Fehr, J. Hinz, H.J. Luthi, M. Wilhelm, Risk management in power markets: The Hedging value of production flexibility, European Journal of Operational Research, 199 (2009) 936-943.
[109] H. Park, J. Lim, Valuation of marginal CO_2 abatement options for electric power plants in Korea, Energy Policy, 37 (2009) 1834-1841.
[110] J. Choi, B.R. Bakshi, T. Haab, Effects of a carbon price in the US on economic sectors, resource use, and emissions: An input–output approach, Energy Policy, 38 (2010) 3527-3536.
[111] M.E. Kraft, Clean air and the Adirondacks: science, politics, and policy choice, Environmental Science & Policy, 1 (1998) 167-173.

[112] K.G. Begg, T. Jackson, S. Parkinson, Beyond joint implementation -- designing flexibility into global climate policy, Energy Policy, 29 (2001) 17-27.
[113] S. Kartha, M. Lazarus, M. Bosi, Baseline recommendations for greenhouse gas mitigation projects in the electric power sector, Energy Policy, 32 (2004) 545-566.
[114] D.J. Crossley, Tradeable energy efficiency certificates in Australia, Energy Efficiency, 1 (2008) 267-281.
[115] S. Napolitano, J. Schreifels, G. Stevens, M. Witt, M. LaCount, R. Forte, K. Smith, The U.S. Acid Rain Program: Key Insights from the Design, Operation, and Assessment of a Cap-and-Trade Program, The Electricity Journal, 20 (2007) 47-58.
[116] S. Napolitano, G. Stevens, J. Schreifels, K. Culligan, The NOx Budget Trading Program: A Collaborative, Innovative Approach to Solving a Regional Air Pollution Problem, The Electricity Journal, 20 (2007) 65-76.
[117] M. Kara, S. Syri, A. Lehtila, S. Helynen, V. Kekkonen, M. Ruska, J. Forsstrom, The impacts of EU CO_2 emissions trading on electricity markets and electricity consumers in Finland, Energy Economics, 30 (2008) 193-211.
[118] B. van Ruijven, L. Hari, D.P. van Vuuren, B. de Vries, The potential role of hydrogen energy in India and Western Europe, Energy Policy, 36 (2008) 1649-1665.
[119] D. Niemeier, G. Gould, A. Karner, M. Hixson, B. Bachmann, C. Okma, Z. Lang, D. Heres Del Valle, Rethinking downstream regulation: California's opportunity to engage households in reducing greenhouse gases, Energy Policy, 36 (2008) 3436-3447.
[120] C.C. Tsao, J.E. Campbell, Y. Chen, When renewable portfolio standards meet cap-and-trade regulations in the electricity sector: Market interactions, profits implications, and policy redundancy, Energy Policy, 39 (2011) 3966-3974.
[121] P. del Río González, F. Hernández, How do energy & environmental policy goals and instruments affect electricity demand? A framework for the analysis, Renewable and Sustainable Energy Reviews, 11 (2007) 2006-2031.
[122] J. Sijm, The impact of the EU Emissions Trading Scheme on the price of electricity in the Netherlands, Energy research Center Netherlands, Petten, The Netherlands, ECN-RX–04-015, (2004).
[123] R. Kannan, N. Strachan, Modelling the UK residential energy sector under long term decarbonisation scenarios: Comparison between energy systems and sectoral modelling approaches, Applied Energy, 86 (2009) 416-428.
[124] H. Winkler, Energy policies for sustainable development in South Africa, Energy for Sustainable Development, 11 (2007) 26-34.
[125] B. Chèze, J. Chevallier, E. Alberola, Emissions compliances and carbon prices under the EU ETS: A country specific analysis of industrial sectors, Journal of Policy Modeling, 31 (2009) 446.
[126] J.H. Keppler, M. Mansanet-Bataller, Causalities between CO_2, electricity, and other energy variables during phase I and phase II of the EU ETS, Energy Policy, 38 (2010) 3329-3341.
[127] A. Sadegheih, Optimal design methodologies under the carbon emission trading program using MIP, GA, SA, and TS, Renewable and Sustainable Energy Reviews, 15 (2011) 504-513.

[128] D. Burtraw, K. Palmer, R. Bharvirkar, A. Paul, The Effect on Asset Values of the Allocation of Carbon Dioxide Emission Allowances, The Electricity Journal, 15 (2002) 51-62.
[129] L. Camille, Impact of Emission Trading on Power Prices: A Case Study from the European Emission Trading Scheme, (2005).
[130] J. Sijm, Options to address EU ETS induced increases in power prices and windfall profits, in: Proceedings of the IEEE Power and Energy Society General Meeting, 2007, pp. 1-2.
[131] J. Sijm, S. Bakker, Y. Chen, W. Lise, H. Harmsen, CO_2 price dynamics: The implications of EU emissions trading for electricity prices and operations, Policy Studies, (2012).
[132] J. Szolgayova, S. Fuss, M. Obersteiner, Assessing the effects of CO2 price caps on electricity investments--A real options analysis, Energy Policy, 36 (2008) 3974-3981.
[133] E.J.L. Chappin, G.P.J. Dijkema, On the impact of CO_2 emission-trading on power generation emissions, Technological Forecasting and Social Change, 76 (2009) 358-370.
[134] A. Newcomer, S. Blumsack, J. Apt, L.B. Lave, M.G. Morgan, Electricity load and carbon dioxide emissions: effects of a carbon price in the short term, in: IEEE Proceedings of International Conference on System Sciences, 2008, pp. 179-179.
[135] E. Delarue, W. D'Haeseleer, Greenhouse gas emission reduction by means of fuel switching in electricity generation: Addressing the potentials, Energy Conversion and Management, 49 (2008) 843-853.
[136] X.R. Li, C.W. Yu, F.J. Luo, S.R. Ren, Z.Y. Dong, Y. Wu, M. K. Meng, K.P. Wong, Optimal Decision Making Model for GENCO under the Emission Trading Scheme, in: IEEE Power and Energy Society General Meeting, 2012, pp. 1-7.
[137] X.Q. Ji, F.S. Wen, Y.S. Xue, Z.P. Liu, Generation investment evaluation in emission trading environment, IET Generation, Transmission & Distribution, 5 (2011) 781-787.
[138] S. Fuss, J. Szolgayova, M. Obersteiner, M. Gusti, Investment under market and climate policy uncertainty, Applied Energy, 85 (2008) 708-721.
[139] D. Most, M. Genoese, A. Eßer, O. Rentz, European electricity and emission market modeling—the design of emission allocation plans and its effects on investment planning, in: International Conference on European Electricity Market, 2008, pp. 539-544.
[140] E. Benz, S. Trük, Modeling the price dynamics of CO_2 emission allowances, Energy Economics, 31 (2009) 4-15.
[141] J. Seifert, M. Uhrig-Homburg, M. Wagner, Dynamic behavior of CO_2 spot prices, Journal of Environmental Economics and Management, 56 (2008) 180-194.
[142] A.A. Rentizelas, A.I. Tolis, I.P. Tatsiopoulos, Investment planning in electricity production under CO_2 price uncertainty, International Journal of Production Economics, 140 (2012) 622-629.
[143] R.E.H. Sims, H.H. Rogner, K. Gregory, Carbon emission and mitigation cost comparisons between fossil fuel, nuclear and renewable energy resources for electricity generation, Energy Policy, 31 (2003) 1315-1326.
[144] N. Strachan, R. Kannan, Hybrid modelling of long term carbon reduction scenarios for the UK, Energy Economics, 30 (2008) 2947-2963.

[145] N. Strachan, A. Farrell, Emissions from distributed vs. centralized generation: The importance of system performance, Energy Policy, 34 (2006) 2677-2689.
[146] B. Naughten, Economic assessment of combined cycle gas turbines in Australia: Some effects of microeconomic reform and technological change, Energy Policy, 31 (2003) 225-245.
[147] S.E. Fleten, K.M. Maribu, I. Wangensteen, Optimal investment strategies in decentralized renewable power generation under uncertainty, Energy, 32 (2007) 803-815.
[148] R. Barth, C. Weber, D.J. Swider, Distribution of costs induced by the integration of RES-E power, Energy Policy, 36 (2008) 3107-3115.
[149] H.D. Kambezidis, B. Kasselouri, P. Konidari, Evaluating policy options for increasing the RES-E penetration in Greece, Energy Policy, 39 (2011) 5388-5398.
[150] K. Verhaegen, L. Meeus, R. Belmans, Towards an international tradable green certificate system--The challenging example of Belgium, Renewable and Sustainable Energy Reviews, 13 (2009) 208-215.
[151] S.G. Jensen, K. Skytte, Simultaneous attainment of energy goals by means of green certificates and emission permits, Energy Policy, 31 (2003) 63-71.
[152] S.G. Jensen, K. Skytte, Interactions between the power and green certificate markets, Energy Policy, 30 (2002) 425-435.
[153] M. Rathmann, Do support systems for RES-E reduce EU-ETS-driven electricity prices?, Energy Policy, 35 (2007) 342-349.
[154] J.D.K. Bishop, G.A.J. Amaratunga, Evaluation of small wind turbines in distributed arrangement as sustainable wind energy option for Barbados, Energy Conversion and Management, 49 (2008) 1652-1661.
[155] H. Jiayi, J. Chuanwen, X. Rong, A review on distributed energy resources and MicroGrid, Renewable and Sustainable Energy Reviews, 12 (2008) 2472-2483.
[156] Available: http://www.PJM.com /
[157] J.V. Issler, L.R. Lima, A panel data approach to economic forecasting: The bias-corrected average forecast, Journal of Econometrics, 152 (2009) 153-164.
[158] P.K. Narayan, R. Smyth, Energy consumption and real GDP in G7 countries: New evidence from panel cointegration with structural breaks, Energy Economics, 30 (2008) 2331-2341.
[159] A. Stan Hurn, K.A. Lindsay, Estimating the parameters of stochastic differential equations by Monte Carlo methods, Mathematics and Computers in Simulation, 43 (1997) 495-501.
[160] H. Tauchmann, Firing the furnace? An econometric analysis of utilities' fuel choice, Energy Policy, 34 (2006) 3898-3909.
[161] G. Zachmann, Electricity wholesale market prices in Europe: Convergence?, Energy Economics, 30 (2008) 1659-1671.
[162] B.P. O Gallachoir, F. O'Leary, M. Bazilian, M. Howley, E.J. McKeogh, Comparing primary energy attributed to renewable energy with primary energy equivalent to determine carbon abatement in a national context, Journal of Environmental Science and Health - Part A Toxic/Hazardous Substances and Environmental Engineering, 41 (2006) 923-937.
[163] C. Lee, C. Chang, New evidence on the convergence of per capita carbon dioxide emissions from panel seemingly unrelated regressions augmented Dickey-Fuller tests, Energy, 33 (2008) 1468-1475.

[164] D.K. Christopoulos, E.G. Tsionas, Financial development and economic growth: evidence from panel unit root and cointegration tests, Journal of Development Economics, 73 (2004) 55-74.
[165] C. Lee, J. Lee, Energy prices, multiple structural breaks, and efficient market hypothesis, Applied Energy, 86 (2009) 466-479.
[166] S. Park, J.P. Hwang, E. Kim, H.J. Kang, A New Evolutionary Particle Filter for the Prevention of Sample Impoverishment, IEEE Transactions on Evolution Computation, 13 (2009) 801-809.
[167] F. Campillo, V. Rossi, Convolution Particle Filter for Parameter Estimation in General State-Space Models, IEEE Transactions on Aerospace and Electronic Systems, 45 (2009) 1063-1072.
[168] S. Ren, J. Bi, Y.F. Fung, X.R. Li, I.T.K. Ho, Freeway traffic estimation in Beijing based on particle filter, in: Sixth International Conference on Natural Computation (ICNC), 2010, pp. 292-296.
[169] P.M. Djuric, J.H. Kotecha, Z. Jianqui, H. Yufei, T. Ghirmai, M.F. Bugallo, J. Miguez, Particle filtering, IEEE Transactions on Signal Processing Magazine 20 (2003) 19-38.
[170] D. Huxley, Dakota Gasification Company CO_2 sequestration verification project--a case study of greenhouse gas reduction verification and marketing, Fuel Processing Technology, 87 (2006) 179-183.
[171] A.J. Conejo, M.A. Plazas, R. Espinola, A.B. Molina, Day-ahead electricity price forecasting using the wavelet transform and ARIMA models, IEEE Transactions on Power Systems, 20 (2005) 1035-1042.
[172] K. Meng, Z.Y. Dong, K.P. Wong, Self-adaptive radial basis function neural network for short term electricity price forecasting, IET Generation, Transmission & Distribution, 3 (2009) 325-335.
[173] Y. Wang, W. Xu, An investigation on the reactive power support service needs of power producers, IEEE Transactions on Power Systems, 19 (2004) 586-593.
[174] H. Wu, C.W. Yu, N. Xu, X.J. Lin, An OPF based approach for assessing the minimal reactive power support for generators in deregulated power systems, International Journal of Electrical Power & Energy Systems, 30 (2008) 23-30.
[175] J. Zhong, K. Bhattacharya, Toward a competitive market for reactive power, IEEE Transactions on Power Systems, 17 (2002) 1206-1215.
[176] W. Yan, J. Yu, D. Yu, K. Bhattarai, A new optimal reactive power flow model in rectangular form and its solution by predictor corrector primal dual interior point method, IEEE Transactions on Power Systems, 21 (2006) 61-67.
[177] F.D. Galiana, I. Kockar, P.C. Franco, Combined pool/bilateral dispatch. I. Performance of trading strategies, IEEE Transactions on Power Systems, 17 (2002) 92-99.
[178] X.R. Li, C.W. Yu, Impacts of emission trading on Carbon, Electricity and Renewable Markets: A review, Proceedings of the IEEE Power and Energy Society General Meeting, 2010, pp. 1–7.
[179] M. Chaudry, N. Jenkins, G. Strbac, Multi-time period combined gas and electricity network optimisation, Electric Power Systems Research, 78 (2008) 1265-1279.
[180] C.X. Guo, J.P. Zhan, Q.H. Wu, Dynamic economic emission dispatch based on group search optimizer with multiple producers, Electric Power Systems Research, 86 (2012) 8-16.

[181] L.H. Wu, Y.N. Wang, X.F. Yuan, S.W. Zhou, Environmental/economic power dispatch problem using multi-objective differential evolution algorithm, Electric Power Systems Research, 80 (2010) 1171-1181.
[182] E. Delarue, P. Van Den Bosch, W. D'haeseleer, Effect of the accuracy of price forecasting on profit in a Price Based Unit Commitment, Electric Power Systems Research, 80 (2010) 1306-1313.
[183] K.P.Wong. Z.Y. Dong, Differential Evolution, an Alternative Approach to Evolutionary Algorithm, in: KY Lee, MA El-Sharkawi (Ed.) Modern Heuristic Optimization Techniques: Theory and Applications to Power Systems, Wiley-IEEE Press, 2008.
[184] M.S. Paolella, L. Taschini, An econometric analysis of emission allowance prices, Journal of Banking & Finance, 32 (2008) 2022-2032.
[185] Available: http://www.aemo.com.au/Electricity/Data/Price-and-demand/Aggregated-Price-and-Demand-Data-Files
[186] Available: http://www.RGGI.org/RGGI/
[187] M.J. Wooldridge, An introduction to multiagent systems, Wiley, 2002.
[188] M. Wooldridge, N.R. Jennings, Intelligent agents: Theory and practice, Knowledge engineering review, 10 (1995) 115-152.
[189] J. Bower, D. Bunn, Experimental analysis of the efficiency of uniform-price versus discriminatory auctions in the England and Wales electricity market, Journal of Economic Dynamics and Control, 25 (2001) 561-592.
[190] D.W. Bunn, F.S. Oliveira, Evaluating individual market power in electricity markets via agent-based simulation, Annals of Operations Research, 121 (2003) 57-77.
[191] D.W. Bunn, F.S. Oliveira, Agent-based simulation-an application to the new electricity trading arrangements of England and Wales, IEEE Transactions on Evolutionary Computation , 5 (2001) 493-503.
[192] A.E. Roth, I. Erev, Learning in extensive-form games: Experimental data and simple dynamic models in the intermediate term, Games and Economic Behavior, 8 (1995) 164-212.
[193] T. Börgers, R. Sarin, Learning through reinforcement and replicator dynamics, Journal of Economic Theory, 77 (1997) 1-14.
[194] J. Hofbauer, K. Sigmund, Evolutionary game dynamics, Bulletin of the American Mathematical Society, 40 (2003) 479.
[195] H. Gintis, Game theory evolving: A problem-centered introduction to modeling strategic interaction, Princeton University Press, 2000.
[196] F. Wen, A.K. David, Optimal bidding strategies and modeling of imperfect information among competitive generators, IEEE Transactions on Power Systems, 16 (2001) 15-21.
[197] M. Yang, W. Blyth, Modeling investment risks and uncertainties with real options approach, International Energy Agency, (2007).
[198] E.B. IEA, International Energy Agency, Paris, France, (2009).
[199] A. Saber, G. Venayagamoorthy, Plug-in vehicles and renewable energy sources for cost and emission reductions, IEEE Transactions on Industrial Electronics, 58 (2011) 1229-1238.
[200] V. Gungor, D. Sahin, T. Kocak, S. Ergut, C. Buccella, C. Cecati, G. Hancke, Smart Grid Technologies: Communications Technologies and Standards, IEEE Transactions on Industrial Informatics, 7 (2011) 529-539.

[201] Z.Y. Dong, K.P. Wong, K. Meng, F. Luo, F. Yao, J. Zhao, Wind power impact on system operations and planning, in: IEEE Power and Energy Society General Meeting, 2010, pp. 1-5.
[202] W.-M. Lin, S.-J. Chen, Bid-based dynamic economic dispatch with an efficient interior point algorithm, International Journal of Electrical Power & Energy Systems, 24 (2002) 51-57.
[203] J.M. Lujano-Rojas, J.L. Bernal-Agustín, R. Dufo-López, J.A. Domínguez-Navarro, Forecast of Hourly Average Wind Speed Using ARMA Model with Discrete Probability Transformation, Electrical Engineering and Control, (2011) 1003-1010.
[204] J. Hetzer, D.C. Yu, K. Bhattarai, An economic dispatch model incorporating wind power, IEEE Transactions on Energy Conversion , 23 (2008) 603-611.
[205] G.M. Masters, Renewable and efficient electric power systems, Wiley-IEEE Press, 2004.
[206] A.N. Celik, Energy output estimation for small-scale wind power generators using Weibull-representative wind data, Journal of Wind Engineering and Industrial Aerodynamics, 91 (2003) 693-707.
[207] J. Carta, P. Ramirez, S. Velázquez, A review of wind speed probability distributions used in wind energy analysis: Case studies in the Canary Islands, Renewable and Sustainable Energy Reviews, 13 (2009) 933-955.
[208] N. Amjady, A. Daraeepour, Mixed price and load forecasting of electricity markets by a new iterative prediction method, Electric Power Systems Research, 79 (2009) 1329-1336.
[209] J. Liu, J. Lampinen, A fuzzy adaptive differential evolution algorithm, Soft Computing-A Fusion of Foundations, Methodologies and Applications, 9 (2005) 448-462.
[210] M. Sissons, P. James, J. Bradford, L. Myers, A. Bahaj, A. Anwar, S. Green, Pole-mounted horizontal axis micro-wind turbines: UK field trial findings and market size assessment, Energy Policy, 39 (2011) 3822-3831.