BUILDING AND INVESTIGATING GENERATORS' BIDDING STRATEGIES IN AN ELECTRICITY MARKET

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Building and Investigating Generators' Bidding Strategies in an Electricity Market

by
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A thesis submitted for the degree of
Doctor of Philosophy
in
Research School of Information Sciences and Engineering
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The Australian National University
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Statement of Originality

To the best of my knowledge and belief, the work presented in this thesis is original and my own work, except as acknowledged in the text. It has not been submitted, in whole or in part, for a degree at this or any other university.

Signature (Candidate)

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Statement of Contribution to Jointly-Published Work

Jointly authored publications forming part of this thesis have been published or accepted or submitted for peer reviewed journals and international conference proceedings. The candidate was principally responsible for designing concepts and algorithms, conducting simulations and numerical experiments, and writing up papers and response to reviewers for these publications.

Publications relevant to the thesis

[1] Y. S. Xue, T. Li, X. Yin, Z. Y. Dong, J. Huang and F. Xue, "A research framework for generalized congestions and market power", *Automation of Electric Power Systems,* Vol. 34, No. 21, pp. 1- 10, Nov. 10, 2010

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Abstract

In a deregulated electricity market environment, Generation Companies (GENCOs) compete with each other in the market through spot energy trading, bilateral contracts and other financial instruments. For a GENCO, risk management is among the most important tasks. At the same time, how to maximise its profit in the electricity market is the primary objective of its operations and strategic planning. Therefore, to achieve the best risk-return trade-off, a GENCO needs to determine how to allocate its assets. This problem is also called portfolio optimization.

This dissertation presents advanced techniques for generator strategic bidding, portfolio optimization, risk assessment, and a framework for system adequacy optimisation and control in an electricity market environment.

Most of the generator bidding related problems can be regarded as complex optimisation problems. In this dissertation, detailed discussions of optimisation methods are given and a number of approaches are proposed based on heuristic global optimisation algorithms for optimisation purposes.

The increased level of uncertainty in an electricity market can result in higher risk for market participants, especially GENCOs, and contribute significantly to the drivers for appropriate bidding and risk management tasks for GENCOs in the market. Accordingly, how to build an optimal bidding strategy considering market uncertainty is a fundamental task for GENCOs. A framework of optimal bidding strategy is developed out of this research.

To further enhance the effectiveness of the optimal bidding framework, a *Support Vector Machine* (SVM) based method is developed to handle the incomplete information of other generators in the market, and therefore form a reliable basis for a particular GENCO to build an optimal bidding strategy.

A portfolio optimisation model is proposed to maximise the return and minimise the risk of a GENCO by optimally allocating the GENCO's assets among different markets, namely spot market and financial market.

A new market price forecasting framework is given in this dissertation as an indispensable part of the overall research topic. It further enhances the bidding and portfolio selection methods by providing more reliable market price information and therefore concludes a rather comprehensive package for GENCO risk management in a market environment. A detailed risk assessment method is presented to further the price modelling work and cover the associated risk management practices in an electricity market.

In addition to the issues stemmed from the individual GENCO, issues from an electricity market should also be considered in order to draw a whole picture of a GENCO's risk management.

In summary, the contributions of this thesis include: 1) a framework of GENCO strategic bidding considering market uncertainty and incomplete information from rivals; 2) a portfolio optimisation model achieving best risk-return trade-off; 3) a FIA based MCP forecasting method; and 4) a risk assessment method and portfolio evaluation framework quantifying market risk exposure; through out the research, real market data and structure from the Australian NEM are used to validate the methods. This research has led to a number of publications in book chapters, journals and refereed conference proceedings.

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List of Acronyms and Abbreviations

AEMO:	Australian Energy Market Operator
AEMC:	Australian Energy Market Commission
AER:	Australian Energy Regulator
ARMA:	Autoregressive Moving Average
CCGT:	Combined Cycle Gas Turbine
CDM:	Clean Development Mechanism
CPRS:	Carbon Pollution Reduction Scheme
DE:	Differential Evolution
DG:	Distributed Generation
EA:	Evolutionary Algorithm
EC:	Evolutionary Computation
EP:	Evolutionary Programming
ES:	Evolutionary Strategy
FIA:	Fuzzy Immune Algorithm
GA:	Genetic Algorithm
GARCH:	Generalized Autoregressive Conditional Heteroscedastic
ISO:	Independent System Operator
JI:	Joint Implementation
LR:	Lagrangian Relaxation
LSE:	Load Serving Entities
LMP:	Locational Marginal Price
MCP:	Market Clearing Price
MLE:	Maximum Likelihood Estimation
MPC:	Market Price Cap
MSE:	Mean Square Error
MTPASA:	Medium-term Projected Assessment of System Adequacy
NEM:	National Electricity Market
NEMDE:	National Electricity Market Dispatch Engine
NEMMCO:	National Electricity Market Management Company (replaced by AEMO from 2009)
NTNDP:	National Transmission Network Development Plan
NTS:	National Transmission Statement
OCGT:	Cycle Gas Turbine
PASA:	Projected Assessment of System Adequacy
PCMI:	Price-Cost Margin Index
POE:	Probability of Exceedence
PSO:	Particle Swarm Optimisation
RBF:	Radial Basis Function
RET:	Renewable Energy Target
SFE:	Supply Function Equilibrium
SMP:	System Marginal Price
SRMC:	Short Run Marginal Cost
SOO:	Electricity Statement of Opportunities
STPASA:	Short-term Projected Assessment of System Adequacy
SVM:	Support Vector Machine
VaR:	Value at Risk
VoLL:	Value of lost load (replaced by MPC from 1 July 2010)
USE:	Unserved Energy

Chapter 1

Introduction

1.1 Research Background

Following the deregulation of the power industry in many countries around the globe, GENCOs are increasingly aware of the need for risk management in order to achieve profit maximisation in the competitive market in which they are participating. The revenue of a typical GENCO comes from the trading in the financial market through various financial instruments and different options, as well as from the spot market. Optimal strategic bidding is a key factor which affects the position of a GENCO's effective trading in the spot market.

In recent years, awareness of global warming has driven increasing numbers of generators running on energy resources other than coal into the market. These include gas fired Open Cycle Gas Turbine (OCGT) and Combined Cycle Gas Turbine (CCGT) plants, hydro, wind farms, solar, nuclear, biomass and other forms of renewable sources. Many of these generators would not be able to supply base load in the traditional electricity market because of their relatively higher cost compared to coal-fired generators. With the likely introduction of an *Emissions Trading Scheme* (ETS), however, they will have competitive advantages over coal-fired stations and will have an increasing share in the electricity spot market. For those new entries, many of which, especially the renewable ones, such as biomass, wind, hydro and so on, are non-scheduled[1] generators in the Australian NEM [1]. Those plants are facing various constraints such as capacity limitation and fuel supply limitations. Therefore, having an optimal risk management strategy is vital for them to achieve maximum profit.

[1] Generating units that were classified as scheduled generating units or non-scheduled generating units prior to 1 May 2008 but could now be classified as semi-scheduled generating units – There is no requirement to apply to reclassify those generating units as semi-scheduled generating units, but there is an incentive to do so.

From the viewpoint of an independent system operator (ISO), a bidding strategy is equally important because they need to run market dispatch and simulation to assist in operations and planning for generation as well as transmission assets.

There are many factors affecting a generator's bidding and risk management strategies in a competitive electricity market. In this thesis, those important factors will be studied in order to form a framework for optimal generator bidding strategies and risk management purpose.

Before going into more details of optimal bidding strategies and risk management, it is important to have an overall picture of the electricity market and the power system behind it.

The power system was considered as "natural monopoly" and it had long been dominated by vertically integrated utilities before deregulation. From the early 1990s, deregulation trend in an electricity market was underway throughout the world. Currently, several semi-deregulated markets are operating in a number of countries, including US, Australia and several European countries [2].

Generally speaking, deregulation aims at decreasing costs and lowering the electricity prices. Competition provides much stronger cost-minimizing incentives than typical regulation and drive suppliers to propose cost-saving innovations more quickly. The innovations include labour saving techniques, more efficient repairs, cheaper plant construction costs and proper investment strategies. While holding down prices, competition also provides incentives for more accurate pricing. Because it imposes the real-time wholesale spot price on the retailer's marginal purchases, wholesale competition should encourage real-time pricing for retail customers. A competitive retailer should have an added incentive to provide the option of real-time retail pricing because that would reflect its costs.

The Australian NEM began operating as a wholesale market since 1998. The establishment of the NEM was the result of extensive consultation and collaboration between the states and the electricity supply industry. The reforms led to the disaggregation of the vertically integrated government-owned electricity authorities into separate generation, transmission, distribution and retail sales sectors in each state.

The goal of the reform process was to increase competition in the industry and provide greater choice for end-use electricity consumers. Widely believed as a successful market so far, the NEM have pursued better network operation and gained greater profits, while it operates one of the world's longest interconnected power systems. More than $10 billion of electricity is traded annually in the NEM to meet the demand of the more than 8 million customers. All these figures indicate that the Australian NEM is a successful example of a deregulated electricity market.

This deregulation has greatly increased market competition by reforming the traditionally integrated power utility into a competitive electricity market, which essentially consists of the day-ahead energy market, real-time energy market and ancillary services market. In a deregulated environment therefore, GENCOs are facing the problem of optimally allocating their generation capacities to different markets for profit maximization. Moreover, the generators have greater risks than before because of the significant price volatility in the spot energy market introduced by the deregulation and there is no regulated prices to guarantee return on investment. To hedge the risks, generators can select a number of financial instruments available in the electricity market, such as forward contracts, futures and options [3]. All the above issues can be considered as a *portfolio selection* problem, which aims at maximizing the return and minimizing the risk of a generator by allocating the generator's assets to different markets and financial contracts. The portfolio selection problem essentially consists of two sub-problems. The first sub-problem concerns designing an optimal bidding strategy for the generator. Due to the deregulation and correspondingly greater market risks, it is important for generators to minimize risk by applying appropriate risk management, which is the second sub-problem of generators' portfolio selection.

The generators' portfolio selection problem involves sophisticated analysis considering the following key factors to achieve the best risk-return trade-off.

- Generators' bidding strategies;
- Generators' risk management and risk attitude;
- Transmission system constraints and their impact on market movement;
- Ancillary services market and system security in a market environment;
- Impact from participating loads on the market; and

- Challenges from environmental market schemes and CPRS.

1.2 Generators' bidding strategies

In a deregulated environment, market participants employ individual trading profit maximization, which is based on their own cost, anticipation of other participants' bidding behaviours and power system operation constraints, rather than cost minimization, as their major objective. The Poolco model is a widely employed model of the electricity market. In this model, generators develop the optimal bidding strategies, which consist of sets of price-production pairs, while the market clearing procedure sets the Market Clearing Price (MCP) [4]. Theoretically, generators should bid at their marginal costs to achieve profit maximization if they are in a perfectly competitive market. However, the electricity market is more akin to an oligopoly market and generators may achieve benefits by bidding with prices higher than their marginal costs. Therefore, developing the optimal bidding strategies is essential for achieving the maximum profit and has become a major concern to GENCOs.

In the Australian NEM, the delivery of electrical energy to market customers comprises a sequence of distinct processes and the Australian Energy Market Operator (AEMO) manages the market according to strict timetables. To enable AEMO's systems to facilitate supply, scheduled NEM generators are required to submit offers to AEMO indicating the volume of electricity [2] they are prepared to produce for a specified price. Price offers of generators indicate a stack of MW levels and the corresponding 10 price bands as illustrated in Fig.1-1 which shows a typical GENCO's bid curve in the NEM.

Bids or offers to supply can be categorized into three different types. Daily bids are submitted before 12:30 pm on the day before supply is required, and are reflected in pre-dispatch forecasts. Generators may submit re-bids up until approximately five minutes prior to dispatch. In doing so, they can change the volume of electricity from what it was in the original offer, but they cannot change the offer price bands.

[2] According to AEMO (in An Introduction to Australia's National Electricity Market, July 2010), there are three types of bids or offers to supply in the NEM: (1) daily bids, (2) re-bids and (3) default bids.

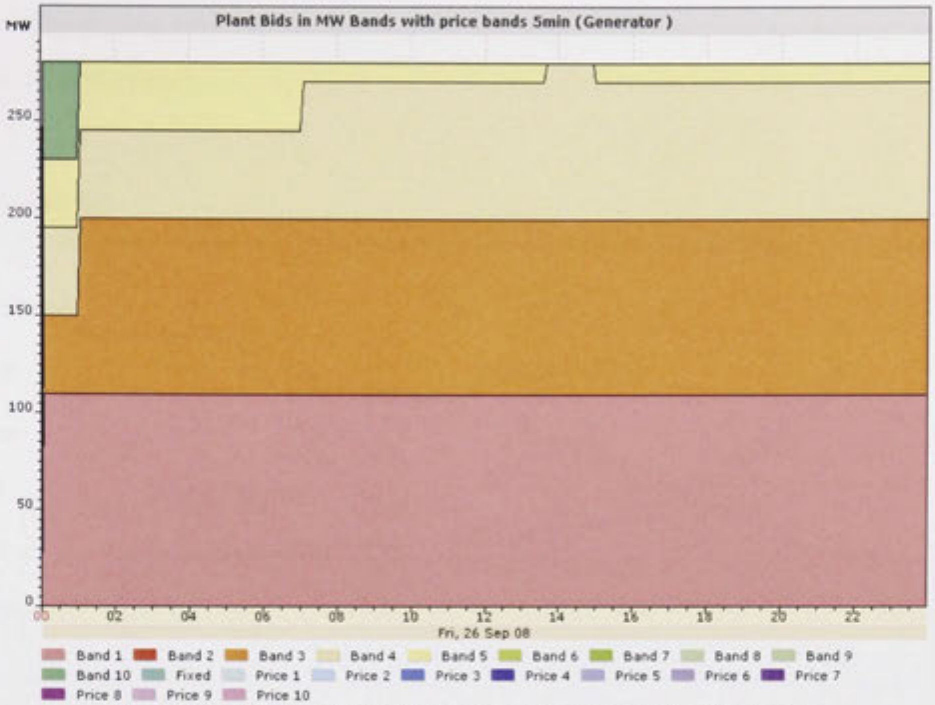

Figure 1-1 Typical GENCO's Bid Curve in the Australian NEM

Default bids are standing bids that apply where no daily bid has been made. These bids are of a 'commercial-in-confidence' nature and, in general, reflect the base operating levels for generators.

Then, the bids from generators are aggregated in *NEM Dispatch Engine* (NEMDE) systems to determine which generators will be dispatched into the market, at what time and at what volume. This process that balances the supply and demand in the market is called *scheduling* and it also prioritizes dispatch based on cost-efficiency of supply. Energy offers from generators are stacked in order of rising price until demand is met. As energy demand increases, more expensive generators are dispatched. The scheduling of generators, however, may be constrained by the capacity of the interconnectors between the regions. When this occurs, more expensive generators will be dispatched to meet the demand within the region and this is also the reason for the difference in the electricity spot price between regions in the NEM. As shown in Figure 1-2, a marginal clearing price is set at the intersection point between the aggregated demand and supply curves for each dispatching period. It should be noted that in the Australian NEM, the demand curve is basically a vertical line because of the application of the single-side bidding protocol. The spot price for a half-hour trading period, which consists of six dispatching periods, would be the average of the prices of the six dispatching periods. All generators winning the auction are paid at the uniform market clearing price.

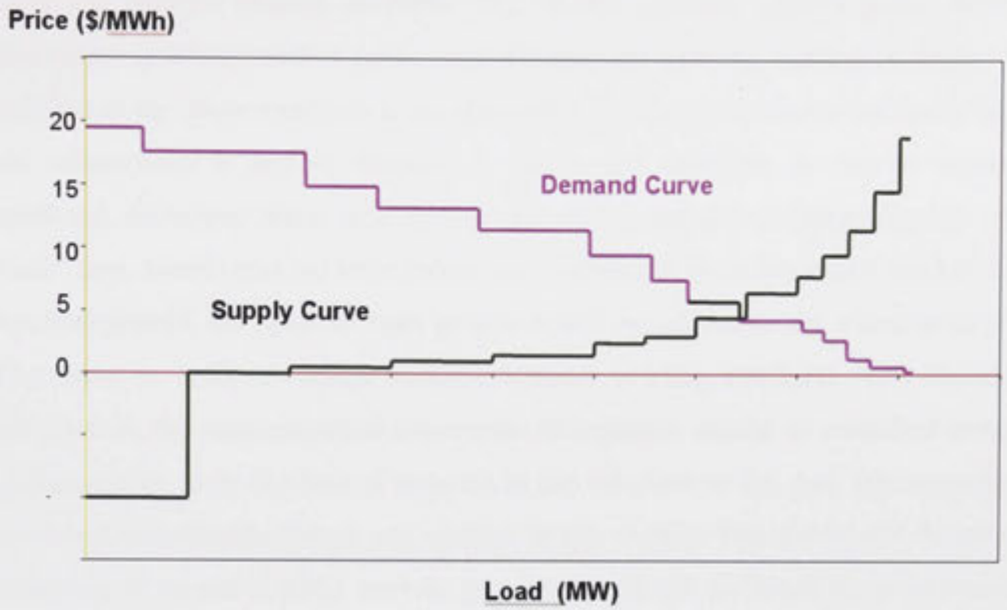

Figure 1-2 Marginal Clearing Price in a 2-Way Bidding Market

At times, the thermal limit and stability limit of the transmission network are expressed as network constraints in National Electricity Market Dispatch Engine (NEMDE), which determines which generators are scheduled to meet demand. When some network constraints are activated, generators may be scheduled out of price order so that demand in a particular area supplied through the network can be satisfied.

Identifying the potential for the abuse of market power is another main objective in investigating bidding strategies. There is a widespread belief among regulators and policy analysts that the deregulation of the electricity generating industry will yield economies in the cost of power supply by introducing competition. However, because the electricity industry has a relatively small number of firms, the benefits that would lower electricity prices may be offset. In particular, in the normal operation of markets, price can be well above the *Short Run Marginal Cost* (SRMC) of production as a result of pricing strategies adopted by rational firms. In economics terms, a supplier has market power when it can raise its price above the level dictated by competition [5]. Thus it is important to have as much information and clarity as possible about these market power effects, so that they can be mitigated before they manifest themselves to the detriment of consumers.

There has been continuous research in investigating and developing generators' bidding strategies [6]. Previous work broadly falls into two categories. The first category of methods employ increasingly sophisticated optimisation techniques to solve the optimal bidding problem. The second category applies game theory to investigate potential market power and develop the optimal bidding strategies. One problem in the above methods is the assumption on rival generators' cost information, bid information or benefit function is public and available or can be accurately predicted. However, these assumptions are often impractical because most of the rivals' cost, benefit and bid information are confidential in an electricity market. Given this background, the profit of each generator will be subject to the information it has. Therefore, in order to design realistic optimal bidding strategies with incomplete information, the unsymmetrical behaviours of suppliers should be modelled correctly. Unfortunately, there is a lack of research in this direction so far. And this research will provide detailed methodology and analysis in this respect. This thesis will describe the designing of proper bidding models, providing methods for handling uncertainties in generating optimal bidding strategies, and developing portfolio optimisation and evaluation frameworks in an electricity market.

Building optimal bidding strategies is a difficult task, because bidding strategies are influenced by a number of complex factors, such as the following:

- Different constraints: Every constraint employed in the bidding decision model influences the final bids of participants, such as technical constraints, network security constraints and regulatory constraints;
- Various financial instruments: Financial derivatives, such as forward contracts futures, and options are employed in an electricity market. Such various types of contracts among suppliers, customers and retailers greatly influence the bidding strategies of generators;
- Generation costs: In a market environment, it is almost impossible to know other generators' cost information;
- Predicted demand and availability of generating units at power plants;
- Predicted rivals' bidding strategies;

- MCPs in the previous trading day: bids in the following trading days would be influenced by the fluctuation of previous market price;

- Forecasting MCPs: the accuracy and reliability of the forecasting are always affected by the high volatility of market price;

- Daily, weekly and seasonal patterns of loads; and

- Types of electricity markets where the generators are participating.

1.3 Research Challenges

The challenges at the outset of this research include:

- Designing proper bidding models for optimal bidding problems in a deregulated electricity market;
- Analysing bidding sensitivities, i.e. how various factors influence the generators' bidding strategy, which is a function of those factors;
- Providing an effective method for estimating and handling the uncertainty in generating optimal bidding strategies in a deregulated electricity market;
- A portfolio optimisation framework to achieve best risk-return trade-off;
- An effective price forecasting framework to provide more reliable market price information;
- A risk assessment method and portfolio evaluation framework to achieve risk aims;

In addition to the above challenges, the industry is facing increasing challenges from global warming concerns as well.

Australia formally signed the Kyoto protocol in 2008 and is aiming at implementing an Carbon Pollution Reduction Scheme (CPRS) in order to reduce greenhouse gas emissions by generators. This will have a significant impact on the Australian generation sector, and possibly change generators' cost structure and the NEM dispatch order of different generators in the spot market. Clean development mechanism (CDM), joint implementation (JI) and carbon offset are among the most important concepts under the Kyoto protocol. This is one of the future topics of this research.

1.4 Research objectives

The main objectives of the research are:

- *Modelling the problem of building and investigating bidding strategies properly.*

Many different issues should be considered in designing proper bidding models. The relevant factors of bidding strategies should be identified and analysed to point out the main factors that affect the decision-making in bidding strategies of individual suppliers. It is essential to build a concise but expressive model to precisely describe the real bidding procedure and to propose an effective solution to optimal bidding problems.

- *Selecting effective algorithms.*

A number of optimization and simulation techniques are currently available. However, they cannot be applied in building bidding strategies directly. So it is necessary to select effective algorithms and determine whether they can be applied with some modifications. Otherwise completely new approaches should be proposed.

- *Estimating and handling electricity market uncertainties in developing generators' bidding strategies.*

As discussed before, there are many factors that may impact generators' bidding strategies. The uncertainties involved in the bidding procedure are introduced by these complex factors. There are methods which may be able to handle the uncertainties; however most of them are in power system analysis areas. Other methods, such as game theory, require a lot of information about the other market players. However, in the real market only a little information is available for all participants. Based on the literature review in this research, only a few literatures have discussed how to estimate and handle the uncertainties in the optimal bidding problem. Therefore, in a deregulated electricity market, we are facing the problem of building optimal bidding strategies by estimating and handling very large market uncertainties with little market information. To solve this problem, it is essential to propose and develop a general optimal bidding strategy framework, which can reliably handle the uncertainties involved in designing the optimal bids.

- *Building a framework for strategic bidding*

As discussed before, a major objective of our framework is to estimate and handle the uncertainties. To accomplish this goal, advanced data mining and statistical techniques will be integrated in the framework. The major steps of the framework are as follows:

  - Employing load and price forecasting techniques to forecast the future load and price;
  - Employing data mining and statistical methods to quantify the market uncertainties;
  - Building bidding scenarios;
  - Self-scheduling in optimizer; and
  - Generating bidding curves for each bidding scenarios.

- *Solving portfolio selection problem and effectively allocating assets to physical and financial markets*

GENCOs are facing the problem of optimally allocating their generation capacities to different markets for profit maximization. Because of the significant price volatility in the spot energy market introduced by the deregulation, generators also need to select financial hedging instruments to hedge the risks. All the above issues can be considered as a portfolio selection problem, which aims at best risk-return trade-off by allocating the generator's assets among physical and financial markets.

- *Proposing a risk assessment method and portfolio evaluation framework*

GENCOs need a proper risk assessment method and portfolio evaluation framework to understand, identify and quantify risk and make well-informed decisions about whether, and how, to deal with this source of uncertainties.

1.5 Contributions

This thesis presents contributions out of the PhD research in the general area of strategic bidding in an electricity market. It provides a rather comprehensive coverage in this topic. The main contributions of this thesis are summarised as follows.

- Comprehensive overview of generation bidding and risk management research

The state of the art of risk management and generator bidding strategies under different market environments are reviewed thoroughly in this thesis. It shows the advances in this area of research and also identifies the needs for further research for topics covered in this thesis.

- New frameworks of building generator optimal bidding strategies subject to market uncertainties and the incomplete information from the market

One of the most challenging difficulties in the generator strategic and optimal bidding problem is handling uncertainties and lack of information from the market where a generator participates. In this thesis, advanced methodologies including risk management and data analysis methods are proposed to handle such uncertainties and lack of information, which still allow generators to achieve optimal and strategic bidding. These frameworks provide very useful tools for developing GENCO's bidding strategies in a deregulated environment.

- Development of generator portfolio selection framework for risk management purpose

In addition to spot market trading, a generator earns even more revenue than spot market from the financial market. The portfolio selection framework proposed in this thesis optimises the portfolio return and risk in order to achieve an optimal portfolio selection for the generator.

- Development of an electricity market price forecasting model

Reliable price forecasting is essential for generator bidding and risk management. A fuzzy Immune Algorithm (FIA) based neural network model is proposed in this thesis to forecast electricity market price series. This forecasting tool forms an important part of the overall risk management and bidding framework proposed in this thesis.

- Development of a new electricity trading risk assessment and management method

Having the portfolio selection tool and basic price forecasting tool is not sufficient unless a proper risk management methodology is available. In this thesis, a data mining based method is proposed to model the volatility of electricity spot market prices and correlate the prices with other relevant factors. The obtained spot price model can then be used to obtain risk neutral process of the spot price, which provides key information for generator risk management. It also allows any electricity derivatives to be included in the risk assessment by generators.

The frameworks incorporate research findings in price modelling, price forecasting, risk management, handling market uncertainty, bidding with incomplete information from the market, and corresponding analytical methods. This framework also includes contributions in optimization algorithms, data mining methods and statistical techniques which are closely related to this research and form an important part of the frameworks. Data mining methods and statistical techniques are employed to estimate future load and price. Statistical methods are used in estimating and handling the uncertainties involved in designing bidding strategies. Effective optimization techniques based on heuristic optimisation methods are developed and used in the frameworks to solve various optimisation problems involved.

The above contributions have led to a number of publications in referred journals, books chapters and conference proceedings related to the thesis. The algorithms developed out of this research can be implemented in generation risk management practices as well.

1.6 Structure of This Thesis

The thesis is organized as follows:

In chapter 1, the background of this research, which includes the electricity market deregulation, market structure and bidding strategies are firstly introduced. Challenges, significances and objectives of this research are also given, followed by a summary of contributions of this research.

In chapter 2, the literature review of the related research is presented. This includes three major parts: (i) the significance and meaning of bidding strategies, (ii) the solution to the optimal bidding problem based on game theory and optimization based methods, and (iii) a general framework of bidding.

Optimisation methods are an important part of the overall research. In chapter 3, a detailed discussion on optimisation and solution methods are presented. They are used to solve optimal bidding strategy problems throughout the research.

In chapter 4, the bidding framework is extended to include functionalities of forming optimal bidding strategies under market uncertainties. Case studies based on realistic market data using the proposed framework are also given. The model has shown to be able to generate useful optimal bidding strategies.

In chapter 5, the framework is further enhanced with the capability of handling incomplete information in an electricity market in order to form optimal bidding strategies by a GENCO. The Australian NEM data are used to test this enhanced framework and the results are presented in this chapter as well.

In chapter 6, a novel portfolio selection approach is proposed. This approach enables GENCOs to allocate their assets in different markets and to optimally use different financial instruments for risk management purpose.

In chapter 7, a new model based on fuzzy IA and RBF neural network is proposed for MCP forecasting purpose. Detailed analysis results based on real market data are given as well. This model contributes to the general framework by providing price forecasting functionalities in a computationally efficient and reliable way.

The price modelling work presented in the previous chapter has been developed and a new risk assessment method and a portfolio evaluation framework are given in Chapter 8. The spot price is modelled by applying a mean-reverting jump-diffusion model and the relationship between spot price and relevant factors is modelled by employing a non-linear regression technique. The risk neutral process of the spot price is also developed and presented in this chapter. Finally, VaR and stress testing methods are employed to quantify the market risk exposure of a given portfolio supported by detailed case studies. This chapter completes the coverage of GENCOs bidding and associated risk management practices in an electricity market.

Chapter 9 concludes this thesis with a summary of the results of this research, followed by the identified future research topics as continuation of the results reported in this thesis.

Chapter 2

State of the Art of Risk Management and Bidding for GENCO in an Electricity Market

A review of related research is given in this chapter to outline the latest findings in the area of generators' risk management and bidding strategies. Existing literature broadly falls into three categories and are summarised in three main sections in this chapter. In section 1, existing research on modelling bidding problems is briefly discussed. These include research in impacts on bidding and risk management from market models, market structure, market types, market power, auction and bidding protocols, economic models and all other relevant market factors. Section 2 reviews the solutions to building and investigating generators' bidding strategies. Two different types of methods, optimization-based methods and game theory-based methods are discussed in detail. The key techniques relevant to this research, including forecasting, optimization, game theory and statistical methods, are briefly reviewed as well. Other issues and findings relevant to this research are presented in section 3, followed by the discussion and conclusion sections.

2.1 Modelling Optimal Bidding Problems

In order to precisely describe the bidding procedure of a specific market, several issues should be carefully considered to design a proper bidding model. These include the market factors relevant to bidding, two different objectives from GENCOs and ISO of bidding models, and all other relevant factors that should be taken into account in analysing the bidding problems.

2.1.1 Major Market Elements

Several major market elements should be considered to construct a concise, but expressive model well describing the market mechanism and bidding procedure. Figure 2-1 depicts a restructured electricity market operation. The Australian NEM follows a similar structure in market operations. Starting from market forecasting to establish demand levels in the NEM, the system operator – AMEO performs a series of activities to facilitate trading of the electricity in the NEM. The key activities include receiving bids from the generators, scheduling and dispatching generators, determining the spot market price, measuring electricity use as well as settling the national electricity market[3]. The research on these elements is briefly reviewed as follows:

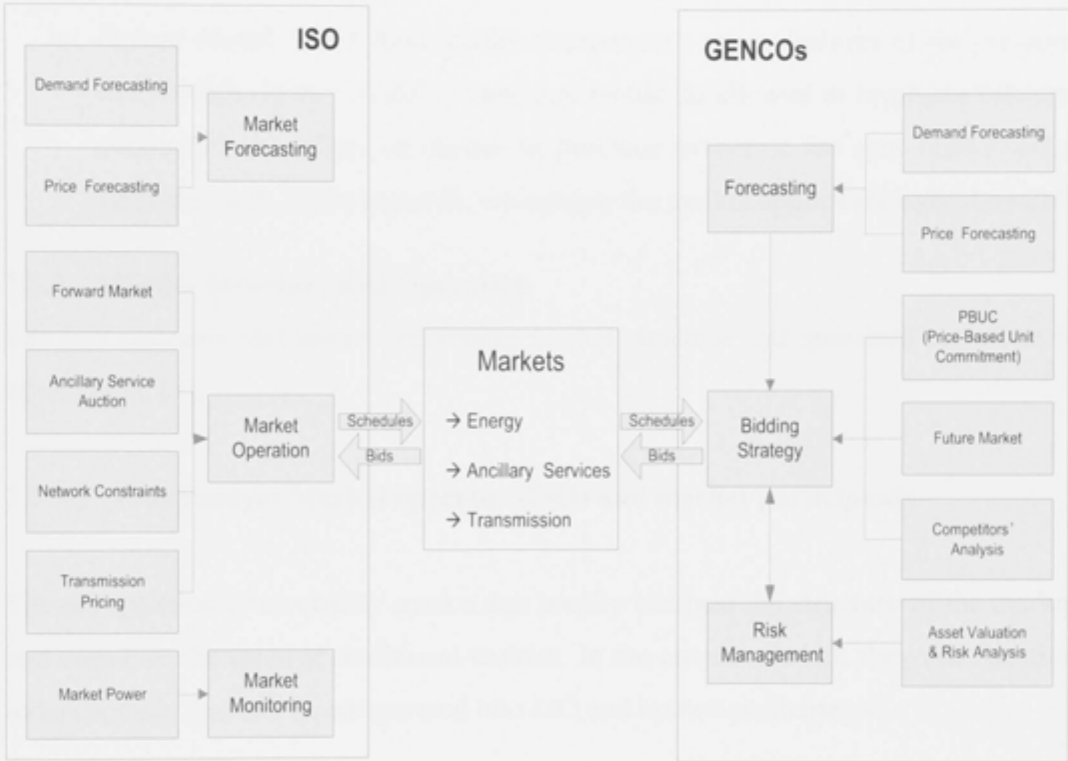

Figure 2-1 Deregulated Electricity Market Operation [3]

2.1.2 Models of Market Mechanism

There are three basic models in a deregulated electricity market [3]:

- *PoolCo Model*. A PoolCo is a centralized marketplace that clears the market for suppliers and customers. ISO in a PoolCo implement the economic dispatch based on maximum social welfare and produce MCP. In this market, a seller who bids too high may lose and may not be able to sell and a buyer who bids

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[3] www.aemo.com.au

too low may not be able to buy. All winning bidders selling electricity are paid at the uniform MCP which is equal to the highest bid of the winners.

- *Bilateral Contracts Model*. Bilateral contracts are negotiable agreements on trading power between suppliers and customers. The bilateral model is very flexible as trading parties specify their contract terms. Bilateral contracts are often used by traders to alleviate risks.

- *Hybrid Model*. The hybrid model incorporates various features of the previous two models. In this model, a customer would be allowed to negotiate bilateral contracts with sellers or choose to purchase power at the spot market price from the pool. In our research, we assume the market applies the hybrid model.

2.1.3 Market Structure and Operation

The key concepts and issues concerning market structure and operation are given in this section, [3].

2.1.3.1 Independent Market operator (ISO) and market participants

The deregulation of electricity market has greatly changed the structure of the market and therefore the roles of traditional entities. In the current market, they can function independently and can be categorized into ISO and market participants.

- *ISO (Independent System Operator)*. ISO is the leading entity and its functions determine the market rules. As an independent control of the grid, ISO administrates transmission tariffs, maintains the system security, coordinates maintenance scheduling, and has a role in coordinating long-term planning.

- *GENCOs (Generation Companies)*. A GENCO operates and maintains existing generating plants. In a deregulated electricity market, generators employ individual trading profit maximization, rather than cost minimization, as their major objective. Therefore, building optimal bidding strategies which consist of sets of price-production pairs is essential for achieving the maximum profit and has become a major concern for GENCOs.

- *DISCOs (Distribution Companies)*. A DISCO distributes the electricity through its facilities to customers in a certain geographical region.

- *TRANSCOs (Transmission Companies)*. A TRANSCO transmits electricity using a high-voltage, bulk transport system from GENCOs to DISCOs for delivery to customers. The transmission system is the most crucial element in an electricity market. A TRANSCO has the role of building, owing, maintaining, and operating the transmission system in a certain geographical region to provide services for maintaining the overall reliability of the electrical system.

- *Customers*. A customer is the end-user of electricity with certain facilities connected to the distribution system or transmission system, according to the customer's size.

- *Other market entities*. There are some other market entities in electricity market, including *RETAILCOs (Retail companies)*, Aggregators, Brokers, and Marketers etc. The introduction of them is omitted here and can be found in [3].

2.1.3.2 Market Types

Based on trading, the market types include the energy market, ancillary services market, and transmission market.

- *Energy market*

The energy market is where the competitive trading of electricity occurs. The energy market is a centralized mechanism that facilitates energy trading between buyers and sellers.

- *Ancillary services market*

Ancillary services are needed for the reliability of power system. In the restructured industry, ancillary services are mandated to be unbundled from energy and are procured through the market competitively.

- *Transmission market*

In a restructured power system, the transmission network is where competition occurs among suppliers in meeting the demands of large users and DISCOs. The commodity traded in the transmission market is called transmission right.

2.1.3.3 Market Processes

In an electricity market, there is a vast amount of information that must be collected and passed between market participants. Some examples are bidding, real time dispatch and metering information. An overview of the market data flows and main systems are shown in Figure 2-2.

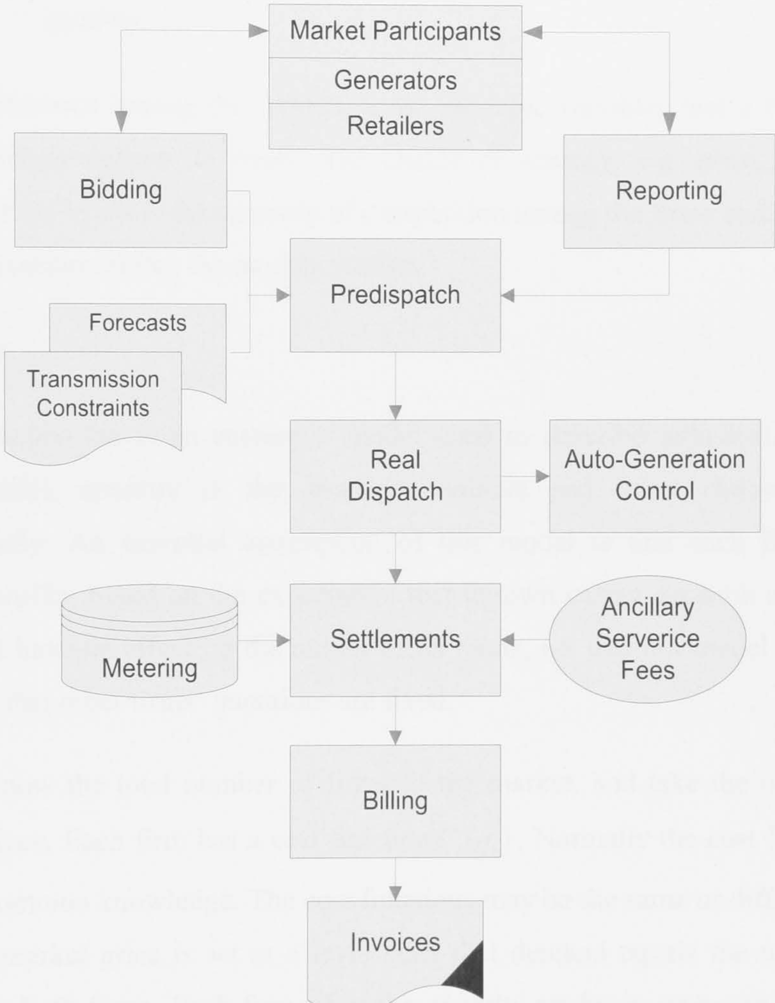

Figure 2-2 Market Information Flow

2.1.4 Models of Market Participant Behaviours

The three static primary equilibrium models applied in an electricity market are the Cournot, Bertrand, and *Supply Function Equilibrium* (SFE) [7, 8]. These models are essential for analysing the behaviours of market participants and their key features are summarised as follows, [9-11]

- *Supply Function Equilibrium* (SFE)

- Entire bid functions are the strategic variables
- Firms choose their supply functions simultaneously
- Under the assumption that other firms' supply functions are fixed
- A market mechanism, e.g. an ISO, then determines price and sets the quantity.

The key difference among the models is the strategic variables that a firm chooses when competing against its rivals. The choice of strategy, e.g. price, quantity, or supply function, impacts the intensity of competition among the firms and the resulting equilibrium outcomes that the models predict.

- *Cournot*

Cournot competition is an economic model used to describe industry structure. In cournot model, quantity is the strategic variable and firms choose quantities simultaneously. An essential assumption of this model is that each firm aims to maximize profits, based on the expectation that its own output decision affects price, but will not have an effect on the output of its rivals, i.e. cournot model is under the assumption that other firms' quantities are fixed.

All firms know the total number of firms in the market, and take the output of the others as given. Each firm has a cost function $C_i(q_i)$. Normally the cost functions are treated as common knowledge. The cost functions may be the same or different among firms. The market price is set at a level such that demand equals the total quantity produced by both firms. Each firm takes the quantity set by its competitors as given, evaluates its residual demand, and then behaves as a monopoly. As a result, the market price is higher than the purely competitive price but less than the monopoly price.

The most common application of Cournot model to an electricity market is based on the presumption that generators do not change their production levels if their competitors' productions are given. The application of Cournot model also because its simplicity and computational flexibility. For example, ISO in POOLCO markets can determine MCP in Cournot model.

The applicability of the Cournot model in the electricity market depends on the different modelling objectives and what market features that the model intends to capture. Whether to use the Cournot model or not must be analysed on a case-by-case basis according to specific market context. GENCOs strategically bid into the market to maximise their profits in an oligopolistic electricity market. This is basically a non-cooperative game, and the solution to the game is Nash equilibrium. At this equilibrium, each player (GENCO) cannot benefit by changing its current strategy while keeping other players strategies unchanged. Cournot model is a common model for oligopolistic market. In [12], an oligopolistic model with Cournot generators and regulated transmission prices is proposed. Transmission constraints and arbitrage are studied when forming Nash-Cournot models are given in [13].

The Cournot model is a quantity setting model and is more appropriate than Bertrand when the number of firms is small.

- *Bertrand* [14]

Bertrand competition is a model of competition used in economics. In this model, firms compete against each other using prices as strategy choices. Specifically, it is a model of price competition between duopoly firms which results in each charging the price that would be charged under perfect competition, known as marginal cost pricing.

The model has the following assumptions. Firstly, it is assumed that firms produce homogeneous products and they do not cooperate. Secondly, firms have the same *marginal cost* (MC) which is constant and possess the capability to supply sufficient output to satisfy demand, so other firms' prices are fixed. Thirdly, all firms compete solely in price to maximize its profit, and choose their respective prices simultaneously and non-cooperatively. There is strategic behaviour by both firms based on their correct expectation of rival's price choice. In addition, demand is linear in this model. Another assumption is that consumers buy everything from the cheaper firm or half at each, if the price is equal.

In classic Bertrand model, price competition yields an equilibrium price equal to marginal cost. In the electricity market, generators face capacity constraints. So to apply the Bertrand model to analyse price competition in electricity market, it is important to account for capacity constraints, as well as for the rationing rule for demand, since the nature of these assumptions may affect the outcome of equilibrium.

Besides, electricity is conducted through wires, and the consumers and generators are connected by transmission lines. Thus the marginal transmission cost, plus marginal production cost add up to total marginal cost. Consequently, generators in two different regions may have different costs. It is possible for generators to increase the price in one region and sometimes the increase is not cost-based.

The applicability of Bertrand model in electricity market depends on the different modelling objectives and what market features that the model is intended to capture. In general, Bertrand competition may realistically competing firms' marginal costs are relatively 'flat' and excess capacity exists. However, whether to use Bertrand model or not must be analysed on a case-by-case basis according to specific market context.

- *Supply Function Equilibrium Model [13]*

In the SFE model, firms bid entire supply functions under the assumption that other firms' supply functions are fixed, and the resulting price equilibriums generally are between the Bertrand and Cournot outcomes. This model can be used to apply imperfect competition in which firms compete with each other through the simultaneous choice of supply functions. Klemperer & Myer developed SFE to model the competition in the market with demand uncertainties. This model is more appealing than the Bertrand and Cournot models because it allows for a strategy space in which competing firms choose entire supply functions.

The major weakness of SFE model is that it is difficult to calculate the equilibriums without restrictive assumptions on the number of firms and the form of firm cost, capacity constraints and the bid (supply) functions.

Different market participant behaviours are important in determining an optimal bidding strategy for a GENCO. These models are considered in methodologies to designing optimal bidding strategies. The key differences of these models are mainly with the selection of strategic variables by a firm when competing against its rivals. They can be summarised as follows:

  - The Cournot model uses quantity as the strategic variable and is more appropriate than Bertrand model when the number of firms is small;

- The Bertrand model uses price as the strategic variable and all firms choose their prices simultaneously and non-cooperatively to compete aiming at profit maximization in a market; and

- The SFE model uses supply function as the strategic variable and can be used to apply imperfect competition in a market.

2.1.5 Market Power

Market power [15] is manifested when an owner of a generation facility is able to exert a significant influence on pricing or on the availability of electricity. If a seller or a group of sellers own the ability to increase the spot price over a competitive level, control the total output, or exclude competitors from a relevant market for a significant period of time, it is defined that the seller or sellers have market power. If a generator is said to have market power, this generator can successfully increase its profits by strategic bidding or by any means other than lowering its costs. Market power may be exercised intentionally or accidentally and could hamper the competition in power production.

So authorities, like ISO, must identify and correct situations in which some market participants exercise market power.

Market power can generally be defined as the ability of a particular seller, or a group of the sellers, to influence the prices of a product to their advantage over a sustained period of time. The *Price-Cost Margin Index* (PCMI) is widely employed to measure the extent of market power abuse in a Poolco. The PCMI quantifies the degree to which the price of a product in a market deviates from what would be its 'perfectly competitive' price. The PCMI is a retrospective indicator of market power, defined as:

$$PCMI = \frac{\text{Actual Product Price} - \text{Perfectly Competitive Product Price}}{\text{Perfectly Competitive Product Price}} \times 100\% \qquad (2.1)$$

where the 'Perfectly Competitive' price is equal to the marginal cost of electricity generation [11] .

The PCMI has a minimum value of zero-implying a perfectly competitive market, and an unbounded maximum value. A PCMI value of 100%, for example, means the price of a product is twice the price that would be expected if the market were perfectly competitive. The PCMI is a level that can be used to measure whether a market is competitive or not.

Market concentration is a measure of the number of firms in a given market. The degree to which market power can be exercised in a given market is largely a function of market concentration. However, this degree also depends upon the structure of the market, the nature of a particular product being sold in this market, the ease of market entry for new firms, and the price elasticity of demand for the product. In this research, the market concentration is quantified by the Herfindahl-Hirschmann Index (HHI), which is defined as:

$$HHI = \sum S_i^2 \qquad\qquad \sum S_i = 100\% \tag{2.2}$$

where S_i is the share of each firm in the market. HHI may be adopted as a proxy for market power in evaluating proposed mergers between firms in the market [16].

In examining market power, according to the type of interaction that they assume about the behaviour of participants, the three models, namely Cournot, Bertrand, and *Supply Function Equilibrium (SFE)*, which have been introduced in Section 2.1.5 can be applied [7].

2.1.6 Auction Methods

Bidding has a strong relationship with the auction mechanism in a market. Bidding strategies should be developed according to market models and activity rules. The auction rules and bidding protocols are the most important two among these rules.

Figure 2-3 illustrates a generator's typical bid curve, which consists of sets of price-production pairs. ISO implements the market clearing procedure and sets the MCP based on all the bids from market participants.

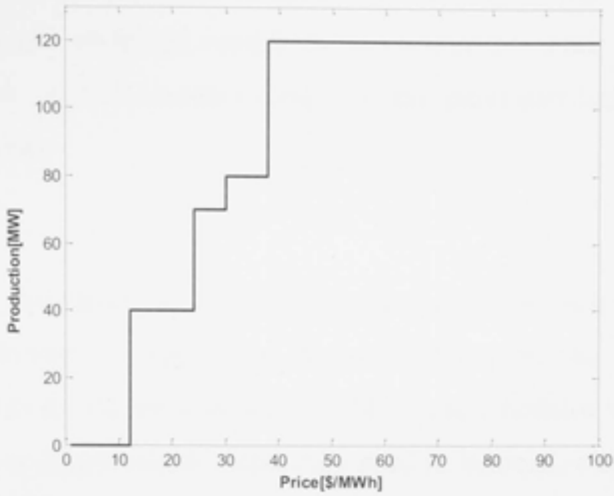

Figure 2-3 A Typical Bidding Curve of a Generation Company in the Australian NEM

An auction is a market institution with an explicit set of rules determining resource allocation and prices on the basis of bids from the market participants. The auction mechanism has been a preferred choice of setting prices for electricity markets. It is an economically efficient mechanism to allocate demand to suppliers, and the structure of electricity markets in many countries is based on auctions.

Auction methods can be categorized into static and dynamic ones. In static ones, the bidders submit sealed bids simultaneously. In dynamic ones, the bidders can observe other competitors' bids and may revise their own sequentially. In terms of discriminating pricing or non-discriminating pricing, bidders in static auctions are paid their offered prices or a uniform price.

Auctions can also be classified as open or sealed-bid. Open auctions may be classified as English (descending) or Dutch (ascending). Sealed-bid auctions are non-discriminating auctions. Almost all operating electricity markets employ the sealed bid auction with uniform market price.

2.1.7 Bidding Protocols

The bidding protocols can be classified as multipart bid or single-part bid according the price components included in bids.

A. Multi-part Bid

A multi-part bid, also called a complex bid, consists of separate prices for ramps, start-up costs, shut-down costs, no-load operation, and energy. In another word, both cost structure and technical constraints are comprised in this kind of bid. By employing a multi-part bid, bid prices, technical constraints and related economic information can be taken into account. A well-known example of the multi-part bid is the England Wales electricity market.

B. Single-part Bid

In a single-part bid, generators bid only independent prices for each trading interval. Based on the intersection of supply and demand bid curves, the market clearing process is conducted to decide the winning bids, MCP and schedules for each dispatch period. This scheme is decentralized. Generators need to internalize all involved costs and technique constraints in developing their bids to make their own unit commitments while in multi-part bids, these will be done by the market operator. The single-part bid has been implemented in several electricity markets, such as Australia, California, Norway, and Sweden.

There are many publications aimed at building bidding strategies for this type of market, which employs single-part bid [17, 18].

2.1.8 Other Factors Relevant to Bidding

In order to deal with the uncertainties in an electricity market, different factors should be considered in developing optimal bidding strategies.

A. Risk Management

In a deregulated market, one of the main factors is risk. In [18-20], different methods for building optimal bidding strategies for generators according to their degree of risk aversion are discussed. Generators compete through both the spot market and financial market. Because of the price volatility in the spot market, generators have to consider the various financial derivatives that they have chosen to achieve their risk management aims when they build their optimal bidding strategies into the spot market [21].

B. Transmission and Technical Constraints

Congestion influence has been considered in [22] and other technical limitations of generating units are comprised in the optimization problem in [23, 24].

C. Coordination with Ancillary Services Market

In [25, 26], developing optimally coordinated bidding strategies in energy and spinning reserve markets is considered. Each generator bids a linear energy supply function and a linear spinning reserve supply function to the energy and spinning reserve market. The two markets are dispatched separately to minimize customer payments. To obtain maximum profit, each generator chooses the coefficient in the linear supply functions, subject to expectations about how his or her rivals will bid.

D. Rivals' Information

Rival's information is another important factor relevant to the bidding problem. Sometimes, it is assumed that rival generators' cost information, bid information or benefit function is public and available. For example, in [24], it is assumed that a generator knows all the other competitors' cost information. In [5], each generator anticipates a value for the bid from each of the other market rivals. In [27], the parameters in rivals' bids are assumed to be available as discrete distributions. In [28], it is assumed that each market participant can estimate its competitors' benefit functions and their minimum and maximum values. However, these assumptions are often impractical because most of the cost, benefit and bid information of rivals are confidential in an electricity market.

Given this background, the profit of each generator will be subject to the information it has. Therefore, in order to design realistic optimal bidding strategies with incomplete information, the unsymmetrical behaviours of suppliers should be modelled correctly. Unfortunately, there is a general lack of research in this direction so far.

E. Single-side and Double-side Auction

Bidding strategies are also subject to the market mechanism. In [29], a framework for testing and modifying bidding strategies by using *Genetic Algorithm* (GA) was proposed. In this chapter, DISCOs and GENCOs buy and sell electricity via double auctions implemented in a regional commodity exchange. In [30], the comparison of efficiency and competitiveness are conducted between double-sides and single-sides (supply-only) auction.

F. System Marginal Price Auction and Pay as Bid Auction [30]

In a *System Marginal Price* (SMP) auction, the final MCPs and profits of GENCOs are determined by the highest bid price being dispatched by ISO through the market clearing process. Unless a particular GENCO sets the price during market clearing process, there is less relationship between the price and the GENCO's own bid price. Consequently, in a perfect competitive market, the increment of GENCO's profit is realized mainly through production cost reduction. The main concern of a GENCO (or more generally an electricity seller) in bidding is how to make sure itself is being dispatched in market clearing; as a result, bidding at lower prices is a less risky approach.

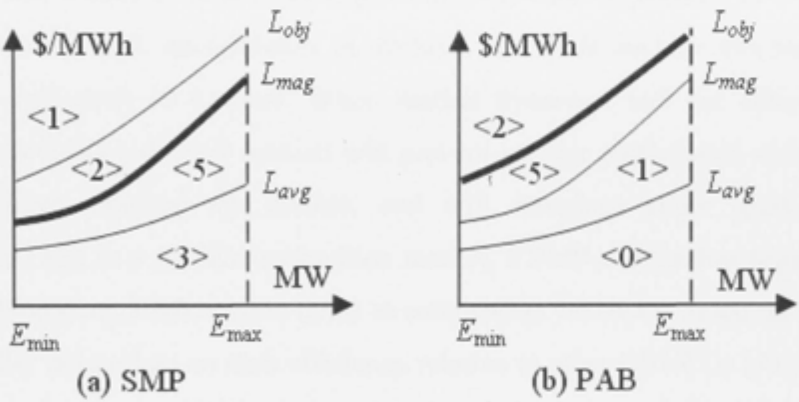

Figure 2-4 Probability distributions of prices for the SMP auction vs. the PAB auction [31]

<0>: least probable, …, <5>: most probable
Bold lines stand for the most probable bid curves of a risk-neutral seller.
L_{avg} : average production price; L_{mag} : marginal price; L_{obj} : price needed to gain desired profit; E_{min} : the lower bound of the bidding capacity, E_{max} : the upper bound of the bidding capacity

For a SMP auction, Figure 2-4 (a) shows the relationship between the amounts of electricity traded vs. prices. The probability variations are assumed in a gradual manner. Among the three bid curves, the marginal price curve L_{mag} is a risk-neutral seller's most probable bid curve (bold line) which aims at reducing the risks of profit losses. In a *Pay as Bid* (PAB) auction, the final market prices are determined by GENCOs' actual bid prices, and thus their profits are determined by themselves. GENCOs have to consider the possibilities of being dispatched at their own bidding prices as well as their profits targets. The distribution of bid prices in a PAB auction market is given in Figure 2-4(b). In a PAB auction market, the most probable bid for a risk-neutral GENCO is L_{obj} in order to meet its profit objective. Under PAB, the GENCOs bear more risks and the bid prices are generally higher than those of SMP auctions. Nevertheless, it should also be noted that because the MCP under SMP is determined by the most expensive bid price dispatched, this introduces an increment of the average price, which is not necessarily always lower than that of the PAB auction market, and vice versa. The relationship between SMP auctions and PAB auctions becomes more complicated if other factors such as social benefits and market efficiencies are considered, [29].

The authors in [30] propose that under competitive and monopoly markets, PAB auction mechanisms can reduce average prices; however, it also reduces demand for electricity. This results in reduction in generation as well. Moreover, in a monopoly market with very high uncertainties in demand, the PAB auction mechanism may cause more reduction in demand. When market dynamics and the entry and exit activities are considered, PAB auction will prevent smaller participants and base-load generators from entering the market, and will introduce more market power. According to [32], in a perfect competition market, a SMP auction has higher market efficiency. Moreover, PAB auction tends to compensate GENCOs based on their price forecast ability rather than on their efficiency relative to other GENCOs [33]. Based on market simulation, authors in [29] also demonstrate that PAB auction leads to higher prices than SMP auction. This is because bid prices are confidential to GENCOs, therefore GENCOs with large market share have more information advantages, and are more likely to bid at higher prices in order to achieve their profit objectives. Although SMP auction is outperformed in consumer surplus by a PAB auction, however, the SMP auction shows more efficiency and it is still difficult to rank the overall welfare between the two approaches [29].

UK's New Electricity Trading Arrangements (NETA) [34], although it has later on not been used for some years, started from 27th March 2001, used a contract market for scheduled power and a PAB auction to replace SMP auction for balancing purposes. It is concluded that the objectives of the auction reform have been achieved, [34, 35]. However, a different view was given by [36] in this regard. Following the California energy crisis in summer, 2000, PAB auction mechanism was tested from 8th December 2000 to 31st January 2001 by the US Federal Electricity Council [37]. During test period, PAB auction was used when the system marginal price went above the soft price cap; and SMP was employed otherwise. The test did not quite meet the expectations and was terminated. According to California ISO[37, 38], PAB auction had virtually no control over market power; most non-utility GENCOs were paid at prices higher than the soft price cap which is actually the single price auction threshold. It is further claimed in [31, 38] that a PAB auction could not solve the problems faced by a SMP auction. A SMP auction is more effective in reducing gaming in a market. It is beneficial for GENCOs with higher efficiency. Currently, SMP auctions are used in most electricity markets around the world, with the help of the bilateral market mechanism.

G. Beta pricing auction

Although SMP is more widely accepted than PAB, there are some areas where PAB outperforms SMP. In order to explore the advantages of both, Beta pricing auction is proposed in [39] where the price paid to the GENCO is a weighted sum of its bids and the MCP. Being a trade-off between the PAB auction and the SMP auction mechanisms, Beta pricing auction, is still complex and carries no clear advantages over PAB and/or SMP.

H. Vickery auction and Vickery-Clarke-Groves auction

Vickery auction refers to the second-price sealed-bid auction [40]. Vickery-Clarke-Groves auction is a generalization of the Vickery auction. The common advantage of them is that that they tend to motivate GENCOs to submit bids more close to their true costs [40, 41]. However they also have some disadvantages:

- The auctioneers are generally not self-funding and may run a deficit, and consequently the auctioneer may cheat;
- There is a danger for the GENCOs to reveal their true cost information to others; and
- There is no MCPs.

These disadvantages make Vickery auction and VCG auction rare in reality. According to the comparisons given in [41], it is hard to find a particular auction mechanism which generally outperforms others. The authors in [31] proposed a new composite auction mechanism to explore the advantages of SMP and PAB mechanisms. Their application is mainly to reduce undesirable price spikes in the market.

I. Different Types of Generators

Empirical analysis about different bidding behaviours of different types of generators in NEM can be found in NEMMCO website [42].

In a deregulated electricity market, generators have freedom to design bidding strategies by taking several factors into account [20]. The main factors influencing bidding strategies include technical limitations of generating units and various categories of contracts. Usually, generators' limitation on energy generation will greatly influence the amount of contracted electricity. Thermal generators enter contracts covering the entire trading day subject to their own technical constraints. If they could not be dispatched and the spot price is higher than the contract strike price, the generator would have to buy the electricity from the pool market to fulfil the contract. So they usually bid at low prices for their contracted electricity in order to be scheduled at their contracted capacity. This would result in revenue losses. Some hydro power stations with limited water resources and gas power stations with high cost of fuel are peak generating units. Most of their costs are recovered by strategic bidding in high price trading intervals in the spot market or entering financial instruments, such as caps, in the financial market. At the same time, they are usually contracted by ISO to provide ancillary services or as system reserve units during peak hours.

2.2 Solutions to Building and Investigating Bidding Strategies and Relevant Techniques

2.2.1 Two Solutions to Bidding Problem

A. Optimization-based Solution

The Optimization-based Solution employs increasingly sophisticated optimization techniques to solve the optimal bidding problem.

In [43], authors solve a two-level optimization problem in their models. In the first level, generators maximize the profit by building a profitable bid and submitting to ISO. In the second level, ISO dispatches power and solves the fundamental problem of market clearing to minimize the overall system cost. Different optimization techniques are used to solve the formulated problems. These techniques include Lagrangian Relaxation [27] , *Optimal Power Flow* (OPF) [43], *Evolutionary Computation* (EC), mainly Genetic Algorithms (GAs) [20], *Evolutionary Programming* (EP) [44] , and

Evolutionary Strategy (ES) [45] , *Monte Carlo* (MC) methods [46] , to mention only a few. A more detailed description of optimisation is given in Chapter 3.

B. Game Theory-based solution

The second category applies game theory to investigate potential market power and develop the optimal bidding strategies. Game theory is a discipline that is employed to analyse problems of conflict among interacting decision-makers. Generally game theory can be classified into two categories, cooperative and non-cooperative. In an electricity market, game theory can be used to analyse how market structures and market rules affect the optimal bidding strategies of GENCOs and how the market participants exercise market power potentially. Apart from that, game theory can also be used to build GENCOs' bidding strategies considering the possibilities of rival's behaviours and study ancillary services pricing.

- *Investigating bidding strategies with Game Theory*

Game theory is widely used to analyse how market structures and market rules affect the optimal bidding strategies of generators and how the market participants exercise their potential market power [16, 24, 47-49]. The authors of [50] apply game theory to simulate the decision making process for defining offered prices in a deregulated environment from the market operator's point of view. There are two kinds of games, namely non-cooperative and cooperative games are considered in this thesis. These methods can be used to analyse the strategic bidding behaviour of generators or other players in a deregulated electricity market. In [24], the authors propose to model generators' bidding strategies by using *supply function equilibrium* (SFE). In [47], the competition among market participants is modelled as a non-cooperative game with incomplete information. This method can be used for electricity pricing. In [49], the authors apply game theory to analyse the power transactions in a deregulated electricity market.

- *Building Bidding Strategies with Game Theory*

In addition to these applications, game theory can also be applied to study ancillary services pricing and to build generators' bidding strategies considering rivals' behaviours [28, 51-53]. A method is proposed in [28] for developing dynamic Nash strategies for *load serving entities* (LSE) in energy multi-markets. This optimal problem is formulated using dynamic game theory. In [51], the authors model the electricity market as an oligopoly market and employ Nash-Cournot strategies to solve the bidding strategy problem. In [52], NE bidding prices could be obtained by using network optimization techniques. In [53], the authors transform the game with incomplete information into a game with complete information by using the Bayes Rule.

2.2.2 **Optimization Techniques**

Optimisation techniques are used intensively in this research. The key optimisation methods in the literature are reviewed here. More detailed analysis on optimisation is given in Chapter 3.

A. Evolutionary Computation (EC)

EC [54] is a type of optimization algorithms originated from natural evolution principles. It is robust, adaptive and has found its application in a wide variety of theoretical and practical problems involving search and optimization tasks. Being different from the traditional calculus based optimization techniques, EC is based on a population of encoded tentative solutions, which are processed with some evolutionary operators to find a good acceptable solution if not the global optimum one. The search and optimization process follows the principle of the survival of the fittest to generate successively better results over generations to finally approximate the optimal solutions. In general, EC algorithms broadly fall into three categories, which have all been successfully applied in power system research. More detailed descriptions of the optimisation methods used are given in Chapter 3 of this thesis.

B. Optimal Power Flow (OPF)

In [55], He and Song present a method for building optimal bidding strategies with taking into account cost-recovery, physical constraints and market price fluctuation resulting from other competitors' bidding strategies. By employing probabilities to represent rivals' bidding strategies, the *Locational Marginal Prices* (LMPs) and schedules could be obtained by a market price simulator based on OPF. The market-oriented *Unit Commitment* (UC) model is applied in this thesis to develop the incremental step-cased price/output bidding curves with the corresponding probabilities. The theory of *Multiple Criteria Decision-Making* (MCDM) has been employed to obtain the optimal bidding strategy with the best compromise among its payoff, market share and probability.

The authors in [56] presented the concept of bids sensitivities which include the first-order derivatives of nodal prices, generation outputs, unit profits and transmission line power flow with respect to each generator's bids. Each generator bids the coefficient of its quadratic cost function. Based on the *Interior-Point OPF* (IPOPF) model, the bids' sensitivities can be derived and each generator can use the IPOPF model to build its optimal bidding strategy with taking into both its own profit maximization and the system securities.

The authors in [43] presented a two-level model of a deregulated electricity market in which an ISO solves an OPF based on the maximization of social welfare and the generators choose their bids in order to maximize their profits under constraints and their dispatch and price obtained from OPF.

Paper [57] focused on the impacts of potential coalitions on GENCOs' bidding strategies in a deregulated electricity market. The generator under consideration is grouped with other generators and non-cooperative and cooperative gaming are respectively applied among and within subgroups. Within each subgroup, the members coordinate their bidding strategies to obtain a common goal. The paper presents an algorithm for the members in each coalition subgroup by introducing bids sensitivities. The method is essentially based on IPOPF model. All the potential combinations of coalition used by the considered generator are given in a priority list.

In [55], the authors established a two-level optimization model based on an IPOPF. This model can be used to obtain bids sensitivities, which can be used to produce optimal bids for an individual generator.

C. Mixed-integer Optimization

Authors in [58] presented an integrated bidding and scheduling framework for building optimal bidding strategies with risk management under a deregulated electricity market. The authors establish a stochastic *mixed-integer optimization* formulation to deal with the MCP uncertainties, bidding risk management, and self-scheduling requirements from each unit. Finally, the selection of bidding curves for both energy and reserve markets has been conducted by using an optimal solution method based on *Lagrangian Relaxation* (LR) and stochastic dynamic programming method.

D. Lagrangian Relaxation (LR)

Using *Lagrangian Relaxation* (LR) as an auction method for bidding may have trouble in choosing some subsets of them for the optimal solution if many units are similar. The authors in [59] presented an alternative bidding strategies to achieve an advantage and provided some sensitivity analysis results.

Zhang et al [27] proposed a method for building optimal bidding strategies and executing self-scheduling when a generator bids part of its energy and self-schedules in New England. With appropriate simplification of the bidding and ISO models, the closed-form ISO solutions are first achieved. With these solutions, the generator's bidding and self-scheduling model is solved by using Lagrangian Relaxation.

E. Ordinal Optimization

Based on the theory of *ordinal optimization*, paper [60] presents a bidding strategy which optimization goal is finding 'good enough' solution. The basic idea here is to use approximate model that describes the influence of bidding strategies on the MCPs. After having got the good enough bids set *S*, the best bid could be obtained by solving full hydrothermal scheduling or unit commitment problems for each of the bids in *S*.

F. Differential Equations

The authors in [61] explore generators' bidding behaviour in electricity auction market under clearing price rule and the sellers' optimal bidding strategies are derived by solving a set of *differential equations* that specify the necessary conditions for bidders to maximize their expected payoffs. A further study shows that the generators have incentives to bid above their production cost. The amount of makeup depends on the probability of winning below and on the margin computed from rivals' cost distribution function, market demand and number of competitors.

G. Learning Automata

In [62], *learning automata* are employed to solve the problem of optimal bidding strategies due to its uncertainties and dynamics in the electricity market. Learning automata are applied to solve this complex optimization problem in this paper. This method has a greatly flexibility and distinct advantages because it is a model-free method.

H. Reinforcement Learning

Paper [63] presents a modified *reinforcement learning* (Q-learning) based on temperature variation and it is applied to build optimal bidding strategy for a generator in a deregulated electricity market. The main advantage of this method is that no rivals' information is required. The authors further discover that even if all generators use this method, they will still stay in Nash Equilibrium.

In [64], the supplier bidding strategy is formulated as a kind of stochastic optimal control problem based on Q-learning algorithm. The presumption here is that there is no supplier that possesses the market power in the competitive day-ahead electricity auction market and they will bid into the market each hour. The authors study the influences of supplier's strategic bidding on the market price under uniform pricing rule and discriminatory pricing rule.

I. Golden Selection Method

Authors in [65] presented a new method for developing optimal bidding strategies with risks taken into account for GENCOs in a pool-based single-buyer electricity market. Each generator bids in the linear supply function for realizing two contradictory objectives: profit maximization and risk minimization. A stochastic model is formulated and Golden Selection Method is employed to solve the problem.

J. Markov Decision Process

The authors in [66] developed an optimal bidding strategy by solving a problem formulated in the framework of *Markov Decision Process* (MDP), which is a discrete stochastic optimization method. The temporal difference technique and actor-critic learning algorithm are employed to optimize the object functions.

In [67], the decision-making problem is formulated as a MDP – a discrete stochastic optimization method. All opponents are modelled by their bidding parameters with corresponding probabilities. A systematic method is developed to calculate transition probabilities and rewards. The presumption is the decision maker is risk-neutral.

2.3 Other Relevant Research

2.3.1 Bidding Strategies Analysis

Paper [68] provides a method for monitoring the generator bidding behaviour. The authors introduce the concept of a strategy curve and use it to represent generator bidding strategies. This bid curve can reveal any deviation in GENCO's bid price from the costs of GENCOs.

The authors in [69] analyse the historical data for the period from May 1, 2002 to May 31, 2003 to identify and examine the behaviour of generators' bidding strategies in the Australian *National Electricity Market* (NEM). Further analysis shows that generators more frequently use capacity offers as a strategic tool than price offers.

2.3.2 Bidding in Transmission Auction Markets

In [23, 70], the authors propose a *Financial Transmission Right* (FTR) bidding model for transmission auction markets with taking risks into account. There are two levels in this model. The upper sub-problem representing bidders and the lower one representing the solution to ISO's FTR market clearing problem for maximizing the revenue obtained from the FTR auction. This problem is solved by developing the sensitivity of a bidder's expected utility with respect to its bidding strategies.

2.3.3 Estimating Rivals' Bidding Behaviours

Paper [71] proposes a methodology for developing bidding strategies for generators by using possibility theory. The authors apply fuzzy set to represent the estimated bidding behaviours of opponents based on historical data, the available production cost data from the power industry restructuring and experts' heuristic knowledge. Hence, a fuzzy programming model is developed to solve the problem.

The authors in [72] present the formulation and features of the *Price Based Unit Commitment* (PBUC) in a deregulated power market. By using the model presents in this paper, GENCOs can maximize their own profits when they are responsible for unit commitment, to commit and schedule their units for selling power, purchasing power, selling spinning and non-spinning reserves. By employing *locational marginal prices* (LMPs) in PBUC, the transmission congestion is incorporated. This paper also represents the derivation of the bidding strategy as a function of generation schedule.

2.4 Discussions

As identified from the literature review, one problem in the existing methods is the assumption that rival generators' cost information, bidding information or benefit function is public or available. For example, in [24], it is assumed that a GENCO knows all the other competitors' cost information. However, these assumptions are often impractical because of such rivals' information are usually confidential in a competitive electricity market. Given this background, the profit of each generator will be subject to the information it has. Therefore, in order to design realistic optimal bidding strategies with incomplete information, the unsymmetrical behaviours of suppliers should be modelled correctly. Unfortunately, there is a lack of research in this aspect so far.

Furthermore, there are complex factors that introduce uncertainties into electricity market and will greatly influence generators' bidding behaviours. Because of the great number of uncertainties that exist in a competitive electricity market, as well the lack of the competitors' information, which is essential for building bidding strategies, previous methods may be able to be applied to solving the decision-making problem in this research, however, the results are still far from satisfactory.

The following chapter will introduce our framework of optimal bidding strategies under market uncertainties and later on enhanced framework to handle incomplete information in the market. The framework will be further enhanced to effectively handle both bidding into the spot market and financial instruments in financial market, which are widely used for risk hedging in a deregulated electricity market. Further improvement of the proposed framework enables it to handle more related influence factors, constraints and uncertainties from the market.

2.5 Conclusion

The literature review of the research on GENCO's optimal bidding strategies and risk management problem was presented in this chapter. Firstly, major market elements are reviewed and discussed. These elements comprise models of market mechanism, market structure and operation, market types, market power, auction and bidding protocols and models of market participant behaviours. How the Australian NEM fits into these market models was commented as well. These market issues are considered in this research to build optimal bidding strategies for generators and investigate generators' bidding behaviours. In the second part, two main solutions to building and investigating generators' bidding strategies are reviewed, namely optimization-based method and game theory-based method. In addition, other key techniques relevant to this research, including forecasting, optimization, game theory and statistical methods are briefly reviewed as well.

Chapter 3

Optimisation Methods

3.1 Introduction

As discussed in Chapter 2, building optimal bidding strategies, solving portfolio selection problem and modelling the risk management are basically optimisation problems and require suitable optimisation methods in order to obtain the optimal solutions. In this chapter, multi-objective optimisation problem is firstly discussed. The detailed description of a number of *Evolutionary Computation* (EC) methods is given subsequently. These EC based methods are used in the following chapters to obtain optimal bidding strategies in a competitive electricity market.

The EC based optimisation methods have been used in this research to form various bidding strategies as a useful global optimisation tool. Some advances in EC are also developed through the research. It is necessary to give an overview of the main EC techniques used in this research.

3.2 Multi-objective Optimisation

3.2.1 Function Optimization Formulation [73]

Optimization methods involve searching the solution space for values of variables which are corresponding to desirable objective function values, being either maximum or minimal. These include bidding problems which can be summarized as to maximize the profit subject to market and system constraints. It is necessary to briefly discuss the formulation for an optimization problem. Because maximization problems can be easily converted into minimization ones, only minimization problems are discussed here.

A general constrained minimization problem can de described as

$$\min_{x \in X^m} y = f(X) = \{f_1(x), f_2(x), \dots, f_M(x)\} \tag{3.1}$$

s.t.

$$\mathbf{g}(\mathbf{x}) \leq 0 \tag{3.2}$$

where $\mathbf{x} = \{x_i\}$, $i = 1, 2, \ldots, n$, is the vector of variables where an optimal value is to be calculated to minimize $\mathbf{y}$; $\mathbf{f}(\mathbf{x}) = \{f_j(\mathbf{x})\}$, $j = 1, 2, \ldots, m_1$, is the vector of objective functions, and $\mathbf{g}(\mathbf{x}) = \{g_k(\mathbf{x})\}$, $k = 1, 2, \ldots, m_2$, is the vector of equality and inequality constraints. Let $m = m_1 + m_2$ and assume that $\mathbf{x}$ is represented as a vector of floating numbers.

This minimization problem can be further represented as

$$\text{Min } \mathbf{F}(\mathbf{x}) \tag{3.3}$$

where $\mathbf{F}(\mathbf{x})$ incorporates the objective function $\mathbf{f}(\mathbf{x})$ and the constraint function $\mathbf{g}(\mathbf{x})$. There are different ways to convert (3.1)–(3.2) into (3.3), among which weighted sum or minmax are two popular approaches as shown in (3.4)–(3.5) with the weighting factors $w_i > 0$.

$$\mathrm{F}(\mathbf{x}) = \sum_{j=1}^{n} w_j f_j(\mathbf{x}) + \sum_{k=1}^{m} w_k g_k(\mathbf{x}) \tag{3.4}$$

$$\mathrm{F}(\mathbf{x}) = \max_{j=1:n,k=1:m} [w_j f_j(\mathbf{x}), w_k g_k(\mathbf{x})] \tag{3.5}$$

For (3.3) and (3.4), the local and global minima can be calculated if the region of realizability of $\mathbf{x}$ is convex, [74]. For (3.3) and (3.5) all local and multiple global minima (if any) can theoretically be located, [75]. For power system problems, the optimization problem may not always be convex, and therefore requires heuristic algorithms such as GAs, PSO or DE to solve it.

Depending on the specific problem to be optimized, the weighting factor can have different practical meanings. For example, in risk management for power system planning, the weighting factor can represent the relative importance of each objective and constraint; it can also represent the probability of occurrence for future scenario while considering their impact on the planning options.

3.2.2 Multi-objective optimisation

An optimisation problem is normally firstly represented by a suitable mathematical model. In reality, many optimisation problems are multi-objective problems. Equations

(3.1) and (3.2) represent a typical general form of minimisation problem with M multiple objectives. The major difference between single objective optimisation problem and multi-objective optimisation problem is that multi-objective optimisation problems, in the multi-dimensional objective space, may have three different instances, i.e., the objectives can be (i) totally conflicting, (ii) non-conflicting, or (iii) partially conflicting, [73, 76]. For totally conflicting problems, there will be no improvements in the optimisation process unless some constraints can be violated. This also means that all feasible solutions are optimal as well. For instances with non-conflicting objectives, the objectives will be correlated; and optimisation based on any objective also leads to optimal solution for other objectives. With some reformulation of the objective function, this type of optimisation problem can be converted into a single objective optimisation problem. In reality, many practical multi-objective optimisation problems, such as optimal bidding problems, belong to the partially conflicting category. For this type of multi-objective optimisation problems, a set of solutions in a Pareto front are of more interest than a single optimal solution. For bidding problems and generation risk management, selection of the optimal solution usually depends on the risk attitude of the decision makers.

Throughout the research, the generation bidding and risk management models are formulated into multi-objective optimization problems with partially incompatible objectives, subject to a list of equality and inequality constraints. For example, a GENCO's profit maximization problem in building bidding strategies can be formulated as an optimisation problem as follows,

$$\max \sum_{t=1}^{T} (\lambda_t * q_t - C_t) \tag{3.6}$$

where λ_t represents the forecasted MCP at hour t in \$/MWh , q_t represents the power produced by the generator at hour t in MW and C_t represents the power production cost at hour t in \$/MW.

The objective function (3.6) is subject to various constraints including, power flow conditions, generation limits, ramping constraints, minimum ON/OFF durations, and fuel constraints, etc.

There are different ways to handle the multiple objectives. A simple approach is to combine all objectives into one by using the weighted sum method. Although this approach is simple in implementation, it does experience difficulties in finding the Pareto-optimal solution, i.e. the set of optimal solutions for all objectives. The "ideal point" or weighted sum metric method is another widely used option. This approach minimizes the distance between the practical solution and the given ideal solution.

Another important multi-objective optimisation technique is the goal programming method. This method requires less computational costs and yet facilitates greater flexibility in handling different types of optimisation problems, including "equal to" and "greater and equal to" type problems. The goal programming method locates the solution by finding solutions that attain the predefined targets. Moreover, if the solutions are not achievable goal programming methods will minimise the deviation from targets instead. For an "equal to" type optimisation problem, goal programming approach can be formulated as follows,

$$\begin{aligned} &goal \quad f_i(x) = t_i \\ &x \in S, \quad i = 1,\ldots,M \end{aligned} \tag{3.7}$$

where S is the feasible search region, and t_i is predefined target for individual objective to be achieved. The ideal targets of this optimisation problem can be obtained by estimation or by independently optimising the objectives before the multi-objective optimisation process. More often, the multiple objectives are of quite different magnitudes and need to be normalised for better optimisation outcomes. There are two commonly used methods for normalisation for this purpose, (i) solving the objectives to find their minima and maxima, or (ii) multiplying proper constant values to the objectives to normalise them approximately within the same order of magnitude. Obviously, the second approach requires less computational complexity and is used in this research.

To solve a specific multi-objective optimisation problem with M objectives, such as optimal bidding problem, deviations from each of the M objectives can be used to formulate the composite objective function for the weighted goal programming approach, [77]:

$$
\begin{aligned}
&Minmize \quad && \sum_{i=1}^{M}(\alpha_i \varsigma_i + \beta_i \tau_i) \\
&Subjectto \quad && f_i(x) - \varsigma_i + \tau_i = t_i \\
& && x \in S \\
& && \varsigma_i, \tau_i \geqslant 0, \text{ and } i = 1,\dots, M
\end{aligned} \tag{3.8}
$$

where, for the i^{th} objective, ς_i and τ_i are the positive and negative deviations respectively, each of them is multiplied by corresponding weighting factors α_i and β_i. The weighting factors are often of equal values in order to ensure the solution stays as close as possible in line with the targets in either direction.

3.2.3 Pareto Front and Optimality

The optimisation solution quality relays on Pareto dominance, which together with Pareto optimality form the basis of multi-objective optimisation [77]. There are three different types of Pareto dominance, (i) weak dominance, which refers to the situation where one objective weakly dominates another objective; (ii) strong dominance, where one objective strongly dominates another objective; and (iii) incomparable dominance, where one objective is incomparable with another objective in the objective space.

Take a minimisation problem for example Figure 3-1 illustrates these three different types of Pareto dominance. Take solution *s* for reference, it strongly dominates the solutions in region (1) because *s* is better for both objectives f_1 and f_2. In region (2), however, the solution is better than *s* for both objectives, and therefore they strongly dominate solution *s*. Solutions along the dotted border lines of different regions are weakly dominated by solution *s* only because it is only better in one of the objectives. Solutions in regions (3) and (4) are incomparable to solution *s* because they are better only in one of the objectives compared with *s*.

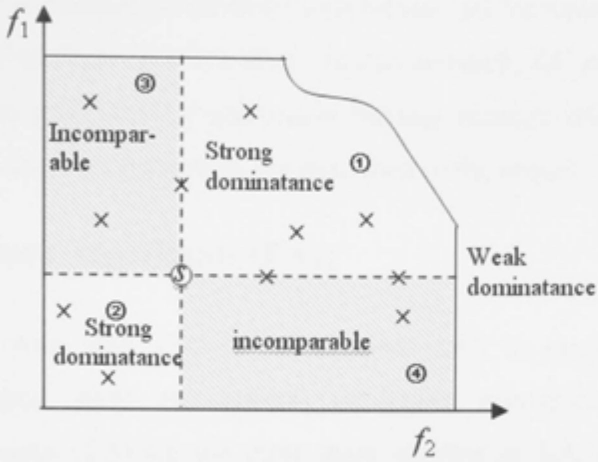

Figure 3-1 Pareto dominance relationship between candidate solutions (×) and a particular solution (s)

The set of dominated solutions forms the optimal Pareto front in the objective space. It represents the trade-off solutions known as the Pareto optimal set. As shown in Figure 3-2, each objective component of any non-dominated solution in the Pareto optimal set can not be improved without degrading at lest another objective components [73, 74].

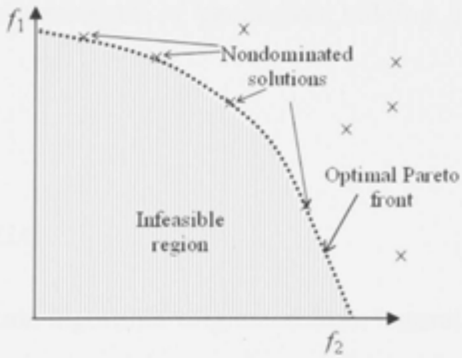

Figure 3-2 Pareto front in the objective space composed of objectives f1 and f2

For real world multi-objective optimisation problems, the optimal Pareto front and trade-off information is usually limited or not known a *priori*. In solving such problems, it is desirable to obtain solutions as much as possible in the Pareto optimal set to form an approximation set as close as possible to the true Pareto optimal set. Ensuring the wide distribution and diversity of the solutions in the approximation set also contributes to the knowledge of true Pareto optimal set. However, this is sometime limited by the available computing resources and depends on the optimisation problem itself. A compromise is often needed.

Once the optimisation problem is properly understood and formulated, the next step is to use optimisation methods to solve them. In this research, EC methods are used in solving optimisation problems for generation bidding strategy and risk management problems. Some of the used algorithms are described in the sequel.

3.3 Evolutionary Algorithms (EAs)

Proposed over 40 years ago, EAs or EC methods refer to stochastic optimization algorithms developed from the natural evolution principles. GAs, EP, and *Evolutionary Strategies* (ES) are the three main streams of EA. Different from the traditional optimization methods, which search the solution space with a single candidate solution point, EAs are based on a population of tentative solutions using evolutionary operators to locate acceptable good solutions if not the global optima. The search and optimization process generates successively better results to approximate the global optimal solutions. The generation introduction of EAs had been given in Chapter 2 of this thesis. In this section, more recent algorithms of *Differential Evolution* (DE) and *Particle Swarm Optimization* (PSO) are given in more details. These methods are used through out this thesis to solve different optimization problems and in forming frameworks of generation bidding and risk management schemes.

3.3.1 Conventional EAs

- *Genetic Algorithm (GA)*

GA[78] [76] is an optimization algorithm originated from natural evolution principles. It is robust, adaptive and has found its application in a wide variety of theoretical and practical problems involving search and optimization tasks. Different from the traditional calculus based optimization techniques, GA is based on a population of encoded tentative solutions, which are processed with some evolutionary operators to find a good acceptable solution if not the global optimum one. The search and optimization process follows the principle of the survival of the fittest to generate successively better results over generations to finally approximate the optimal solutions.

In the implementation of GA, a population of candidate solutions, which are referred to as chromosomes, evolves to satisfactory solutions, approximating the global solution in finite generations through genetic operators of reproduction, mutation and crossover.

Among the many factors affecting the robustness and effectiveness of GA, population size and the total number of generations are among the most important ones. When the population size is increased more than its minimum size, the computation time for the evolution process may increase if the number of generations required for obtaining the optimal solutions cannot be reduced sufficiently. For GA, the minimum population size can be reduced by forming high quality chromosomes in a population. A balance has to be made so as to explore the search space with the minimum number of individuals in order to save computational costs. The program flow chart of a typical GA is given in Fig. 3-3, [79, 80].

The authors of paper [45] address the problem of developing optimally coordinated bidding strategies for competitive generators in energy and spinning reserve markets which are dispatched separately to minimize customer payments. The presumption in this paper is that each generator bids a linear energy supply function and a linear spinning reserve supply function into the energy and spinning reserve markets and each generator decides the coefficients in the two linear supply functions to maximize his/her profits, subject to expectation about other competitors' bids. The problem is described as a stochastic optimization model and finally be solved by using GA.

The authors in [81] present the problem of developing optimal bidding strategies for generators in a day-ahead energy market. Each generator decides its coefficients in the linear energy supply functions to maximize total benefits in the schedule day based on the expectations about rivals' bidding strategies. The authors propose an overall bidding strategy based on two bidding schemes, namely 'maximum hourly-benefit bidding strategies' and 'minimum stable output bidding strategies'. Stochastic optimization models are first developed to describe these two different bidding schemes. Finally, the overall bidding strategy is developed by a GA for the day-ahead market.

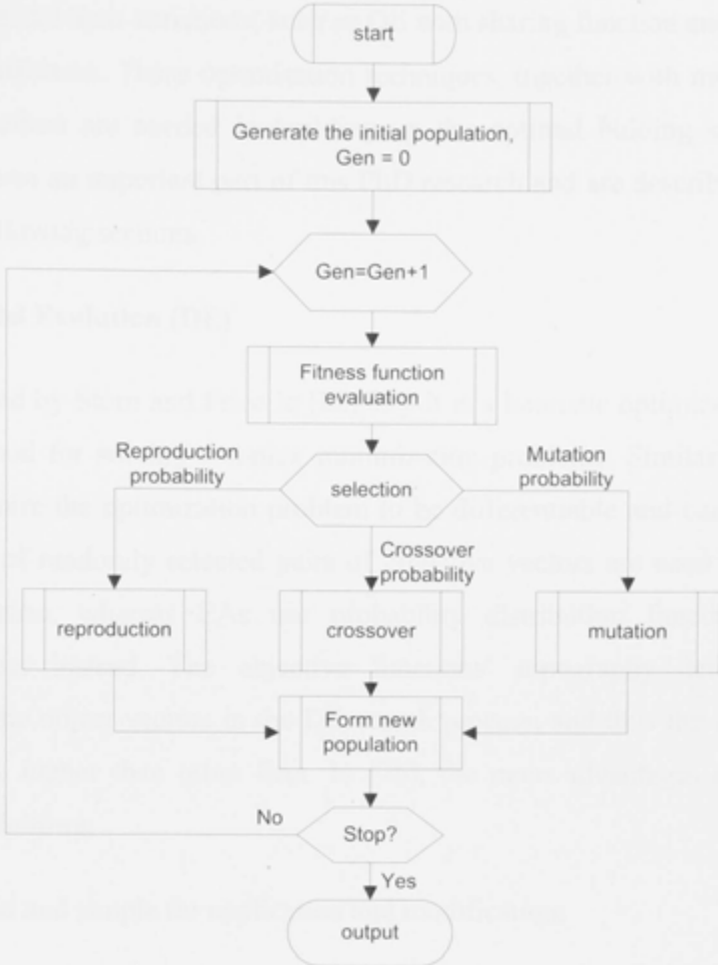

Figure 3-3 A typical Genetic Algorithm (GA) [76]

- *Evolutionary Programming (EP)*

In [44], the authors propose an optimal bidding strategy for a generator under a day-ahead market. The selection of parameters for the energy market and reserve market when taking generating technique constraints into account is formulated as a stochastic optimization problem. Finally the problem is solved by using EP.

- *Evolutionary Strategy (ES)*

Paper [45] presents an evolution strategy for generator bidding in day-ahead electricity auction market based on the (1+1)-ES algorithm. The authors explore the influence of generators' types on the market average bidding price.

- Other EC methods

Other EC based optimisation methods have also been applied in various generation planning and risk management areas. Such techniques include DE, PSO, *Memetic*

Algorithm (MA) and their variations, such as DE with sharing function and online PSO, for better performances. These optimisation techniques, together with multi-objective optimisation method are needed in building up the optimal bidding strategic in a market. They form an important part of this PhD research and are described in greater details in the following sections.

3.3.2 Differential Evolution (DE)

DE was proposed by Storn and Price in [82, 83]. It is a heuristic optimization method basically designed for solving complex minimization problems. Similar to the EAs, DE doesn't require the optimization problem to be differentiable and convex. In DE, the differences of randomly selected pairs of objective vectors are used to guide the mutation operation, whereas EAs use probability distribution functions for the mutation process instead. The objective functions' topography determines the distribution of the object vectors in the DE search process, and thus the efficiency of DE is generally higher than other EAs. In [76], the main advantages of a DE are summarized as follows,

- DE is fast and simple for application and modification;
- It has effective global optimization capability;
- It has parallel processing nature;
- A DE operates on floating point format with high precision;
- It is an efficient algorithm without sorting or matrix multiplication;
- DE uses self-referential mutation operation;
- DE is effective on integer, discrete and mixed parameter optimization;
- IT has the ability to handle non-differentiable, noisy, and/or time-dependent objective functions;
- A DE operates on flat surfaces; and
- It has the ability to provide multiple solutions in a single run and effective in nonlinear constraint optimization problems with penalty functions.

Similar to other EAs DE also uses the initial population generation, mutation, recombination and selection operators to search the optimal solutions. The fundamentals of DE are reviewed below.

(1) Initial Population Generation

A population of N parameter vectors for each generation is used in DE. At generation G, the population P^G is composed of $\mathbf{x}_i^G$, $i = 1, 2, \ldots, N$. The initial population P^{G0} can be chosen randomly under uniform probability distribution if there is no information about the optimization problem *a priori*. The following equation can be used to generate the initial population,

$$\mathbf{x}_i^G = \mathbf{x}_{i(L)} + rand_i[0,1] \cdot (\mathbf{x}_{i(H)} - \mathbf{x}_{i(L)}) \tag{3.9}$$

where $\mathbf{x}_{i(L)}$ and $\mathbf{x}_{i(H)}$ are the lower and higher boundaries of $\mathbf{x}_i = \{x_{j,i}\} = \{x_{1,i}, x_{2,i}, \ldots, x_{d,i}\}^T$. It should be noted that, if there is available information about the problem to be optimized, some preliminary solutions can be included to the initial population by adding normally distributed random deviations to the nominal solution. This will lead to faster convergence toward the optima.

(2) Mutation and Recombination

DE uses parameter vectors throughout its search process. A new parameter vector is formed by adding the weighted difference between two individuals with a third individual. The new vector is then evaluated and compared with a predetermined individual in search for a better individual. If the new parameter vector is better than the predetermined one, it will replace the predetermined parameter vector. In every generation, the best parameter vector is evaluated to track the progress. The search distance and direction information of the population is used to build the random deviations for DE in its search process.

For each dimension at dimension $j \in [1, d]$, the process of generating a child vector based on the distance information of parent parameter vectors can be described in the following equation, which is referred to as scheme DE 1 by Storn and Price in [82],

$$x' = \mathbf{x}_{r3}^G + F \cdot (\mathbf{x}_{r1}^G - \mathbf{x}_{r2}^G) \tag{3.10}$$

where $r1 \neq r2 \neq r3 \neq i$ are random integers. They are used to index the current parent object vector. Clearly, the population size N must be greater than 3. $F \in (0, 1+)$ is a real constant positive scaling factor which controls the scale of the differential variation $(\mathbf{x}_{r1}{}^{G} - \mathbf{x}_{r2}{}^{G})$ – see Fig. 3-4.

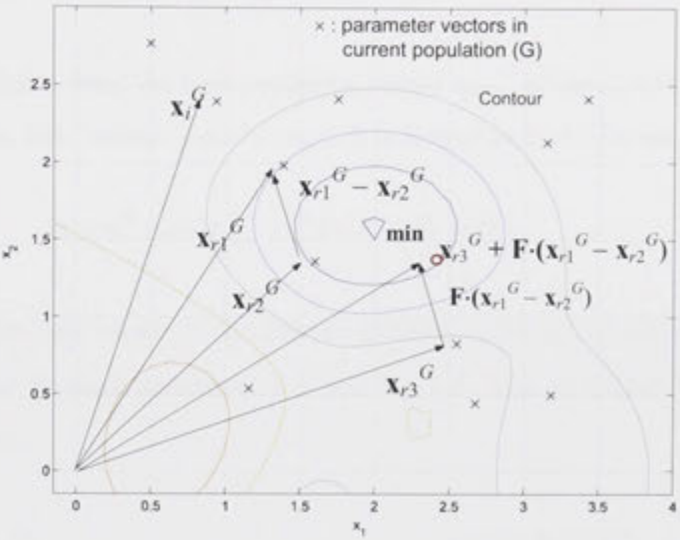

Figure 3-4 The child vector creation procedure with DE 1, where the closed lines are the contour toward the minimal solution point [76]

The crossover constant $CR \in [0,1]$ is used to select the new vector to ensure the search diversity. Some of the new vectors will be used as child vectors for the following generation. The process of creating new candidates is described in the following pseudo-code

<u>Pseudo-code of the creation procedure in DE (mutation and recombination):</u>

Mutation and recombination:

For each individual j in the population

Generate 3 random integers, r_1, r_2 and $r_3 \in (1,N)$

and $r_1 \neq r_2 \neq r_3 \neq j$

Generate a random integer $i_{rand} \in (1,N)$

For each parameter i

If $rand(0,1) < CR$ or $i = i_{rand}$

$\mathbf{x}'_{i,j} = \mathbf{x}_{i,r3} + \mathrm{F}\cdot(\mathbf{x}_{i,r1} - \mathbf{x}_{i,r2})$

Else

$\mathbf{x'}_{i,j} = \mathbf{x}_{i,j}$

End If

End For i

End For j

To include the impact from the best candidate vector $\mathbf{x}_{best}{}^{G}$ of the current generation in the search process, DE2 scheme can be used. It is formulated as follows,

$$x' = \mathbf{x}_i^G + \lambda \cdot (\mathbf{x}_{best}^G - \mathbf{x}_i^G) + F \cdot (\mathbf{x}_{r1}^G - \mathbf{x}_{r2}^G) \tag{3.11}$$

In this scheme, the best vector of the current generation provides extra greediness for the search process through parameter λ – see Fig 3-5. This is useful for non-critical objective functions.

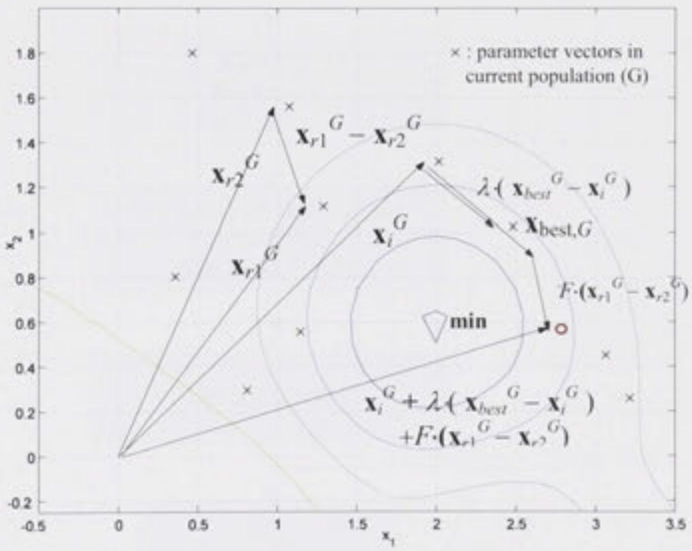

Figure 3-5 The child vector creation procedure with DE 2 from vectors of current generation, where the closed lines are the contour toward the minimal solution point [76]

(3) The overall DE search process

Similar to other EAs in selecting new candidate vectors, DE compares each new vector $\mathbf{x'}$ with the previous vector $\mathbf{x}_i$. The original vector $\mathbf{x}_i$ is replaced by the new vector $\mathbf{x'}$ into the next generation if the new vector results into a better optimization objective. The overall flow chart of a typical DE is given in Figure 3-6.

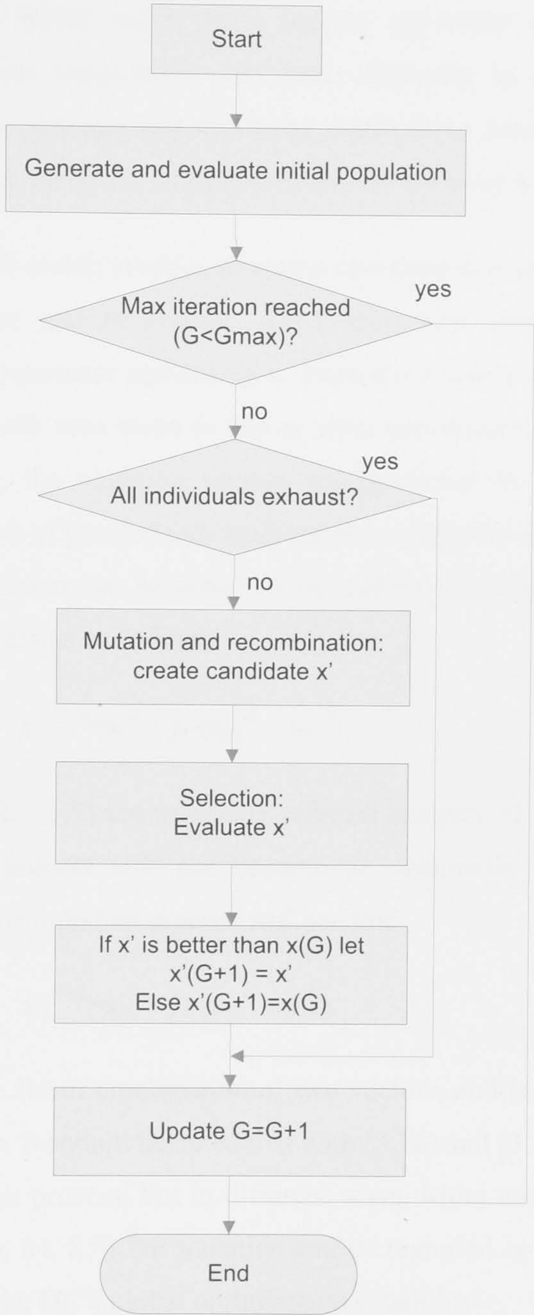

Figure 3-6 Flow Chart of A Typical DE

(4) Main DE Operations

DE relies on a number of operations to guide its search process. The main ones include encoding, mutation, cross-over, selection and population size selection.

Encoding - Instead of binary encoding method, floating point numbers are used to encode the parameter variables in DE. It is also used in the DE mutation process as well. This is a major advantage over other conventional EAs which rely on binary encoding schemes, which suffer from limited capability to effectively represent variables of different magnitudes, and have difficulty in preserving continuum's topology where the scheme may not map consecutive binary integers to adjacent values of the original variables. Such difficulties do not exist with DE.

Mutation - In the DE search process, mutation operation is to enable search diversity in the parameter space and to provide search directions leading to possibly better solutions. For real parameter optimization, mutation is realized by adding a randomly generated number with zero mean to one or more parameters of an existing vector. In DE search process, the mutation vectors are generated by adaptively scaling and correlating the output of pre-defined, multivariate probability distribution. For the G-th generation, DE mutation can be achieved by adding the weighted difference of two randomly selected vectors as follows,

$$\mathbf{x}'^{G+1}_i=\mathbf{x}_i^G+f_1\cdot(\mathbf{x}_{r1}{}^G-\mathbf{x}_{r2}{}^G) \tag{3.12}$$

where $r1, r2 \in \{1, 2,\ldots, N\}$ are randomly selected integers. $r1 \neq r2 \neq i$, which ensures that the mutation process will not become an arithmetic crossover process. For example, if $r2 = i$, the mutation process will become

$$\mathbf{x}'^{G+1}_i=\mathbf{x}_i^G+f_2\cdot(\mathbf{x}_{r1}{}^G-\mathbf{x}_i{}^G) \tag{3.13}$$

Clearly this is just a linear combination of two vectors, and is not mutation but rather arithmetic crossover. It should be noted that both (3.12) and (3.13) provide useful input in guiding the search process, but in different ways. More complex mutation process can be found in [76, 84, 85]. DE mutation can be regarded as globally correlated and therefore increases the DE's global optimization capability.

Crossover or recombination – crossover or recombination is only a complementary process for DE. It is designed to reinforce prior success in forming the next generation. Discrete recombination is the basic recombination method. Crossover constant CR can be used to determine if the newly generated individual is to be recombined. By combining (3.12) and (3.13), mutation and crossover process can be formed,

$$\mathbf{x}'^{G+1}_i=\mathbf{x}_i^G+f_2\cdot(\mathbf{x}_{r3}{}^G-\mathbf{x}_i{}^G)+\ F\cdot(\mathbf{x}_{r1}{}^G-\mathbf{x}_{r2}{}^G) \tag{3.14}$$

where $r1 \neq r2 \neq r3 \neq i$, and F is the mutation constant and $f_2 \in [0,1]$ and remains constant though the evolution process. It controls the crossover constant. Clearly, $f_2 = 1$ is the discrete recombination model with $CR = 1$, and $f_2 = 0$ is the mutation only model.

Population size – both fixed and variable population size can be used in DE's search process. Smaller population size corresponds to fast convergence, but may be subject to premature convergence or stagnation. A population size of between 2 ~ 100 times of the problem dimension will usually generate satisfactory results.

In addition to the fundamentals of DE described above, there are also other advanced DEs introduced in the literature. These include parallel differential algorithm,[84], and direction hybrid DE, [86]; DE for constrained optimization,[87]; pareto-based multi-objective DE, [85]; variable scaling hybrid DE, [88]; and sharing function enhanced DE, [89].

DE has a clear structure in its search process, and yet with very strong global search capability and high efficiency compared with conventional EAs. It is used in a number of applications in this thesis.

3.3.3 Particle Swarm Optimisation (PSO)

PSO is another recently developed EA. PSO was first introduced in 1995 by Kennedy and Eberhart in [90]. It was originated from the simulation of bird flocks behavior. One of the commonly used bird flock or fish school models for PSO studies is the one developed by [91]. In this model, birds start searching by flying around with no particular destination and in spontaneously formed flocks until one of the birds fly over the roosting area, or the good solution point within the search domain. In a PSO algorithm, Similar to other EAs, PSO is first initialised with a population of random candidate solutions. It then searches for optima by updating each generation – see Figure 3-7. However, different from other EAs such as GAs, PSO has no evolutionary operators such as crossover and mutation. Instead, each particle will fly over a solution space and try to find the best solution depending on its own discoveries and past experiences of its neighbours.

The PSO method can be described by the following two equations,

$$x_i^{G+1} = x_i^{G+1} + V_i^{G+1} \tag{3.15}$$

$$
\begin{aligned}
V_i^{G+1} &= \omega V_i^G + c_1 r_1 \times \left(P_{besti}{}^G - x_i^G\right) \\
&\quad + c_2 r_2 \times \left(G_{besti}{}^G - x_i^G\right)
\end{aligned}
\tag{3.16}
$$

where V_i^G is the velocity of individual i at iteration G, ω, c_1 and c_2 are weight parameters/factors, r_1 and r_2 are random numbers between 0 and 1, x_i^G is the position of individual i at iteration G; $P_{besti}{}^G$ is the best position of individual i until iteration k, and $G_{besti}{}^G$ is the best position of the group until iteration G. Eqn (3.15) defines the movement of each individual with the velocity defined in (3.16). Clearly the PSO method has comparable computational efficiency with DE.

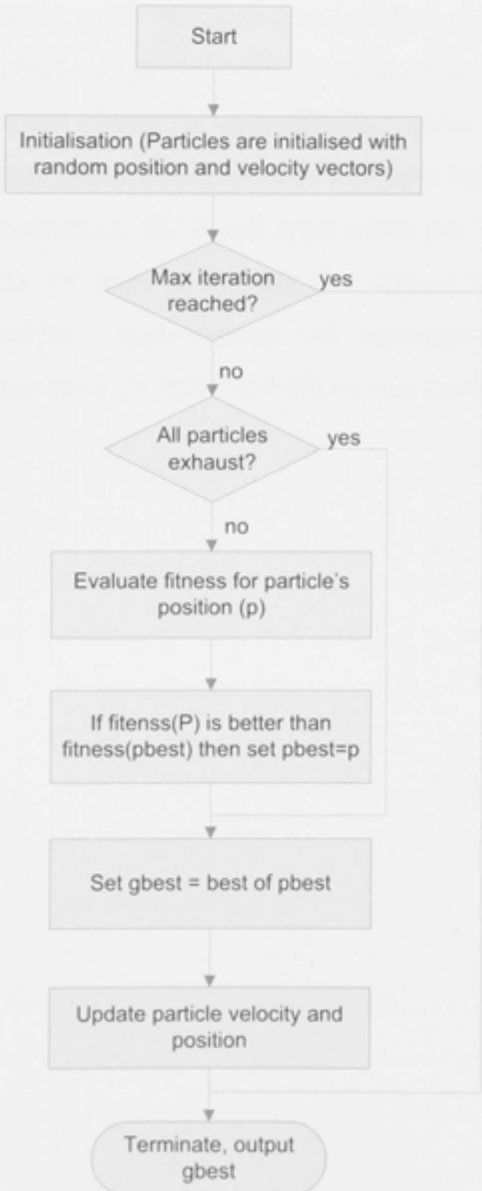

Figure 3-7 Flow Chart of A Typical PSO

In this thesis GA, DE and PSO are used at different occasions for locating the optimal bidding solutions.

3.4 Conclusions

Building optimal strategic bidding, solving portfolio selection problems and modelling risk management are basically an optimisation problem which requires efficient optimisation tools in order to locate the optimal solutions. In practice there are a number of available tools for such purpose, including linear programming, nonlinear programming, and EC based methods. In an electricity market, the GENCOs, when developing their bidding strategies, allocating asset to solve portfolio selection problems, and implementing risk management to achieve risk aims, need to consider a number of factors and find the optimal ones. In some cases, optimisation problems can be approximated by linear solvers for computational speed. However, in other cases, the problem may become too complex (such as non-convexity) to be tackled by linear solvers. In such circumstances, EC based approaches can be used. In the following chapters, different EAs are used in forming the optimal bidding strategies, solving portfolio selection problem, implementing risk management for a GENCO in an electricity market to maximise its profit and effectively manage its risk under different circumstances.

Chapter 4

A framework of optimal bidding strategy with market uncertainty

In this chapter, a comprehensive framework of building optimal bidding strategies under highly uncertain market conditions is proposed. The motivation and intuition of the proposed framework are presented first, followed by detailed descriptions. *Generalized Autoregressive Conditional Heteroscedastic (GARCH)* model and GA, which are incorporated in the framework, are briefly discussed for completeness. The results based on simulations using realistic market data are finally presented to demonstrate the effectiveness of the proposed approach.

4.1 Introduction

As stated in Chapter 2, many approaches are present for designing optimal bidding strategies. However, these methods have a number of limitations. A major problem in existing methods is assuming that some market information, which is unknown in practice, is public and available. For example, existing approaches usually assume rivals' cost information is publicly available, while this information is actually confidential. Some of the existing approaches assume that the *MCP* is a known factor for market participants, or assume that the forecasted electricity price is very accurate. In practice however, these assumptions are always violated because of the extreme volatility and uncertainties of the electricity price. The incomplete market information and many other uncontrollable factors cause significant uncertainties in designing bidding strategies. To design the optimal bidding strategies, the market uncertainties should be accurately estimated and taken into account in the designing procedure. Moreover, in such an uncertain market environment, bidding strategies depend not only on market rules, market variables and competitors, but also on the participant's attitude towards risk. A risk averse would choose to sell the electricity at a low price to assure it will be dispatched. A risk seeker, on the other hand, prefers high profits which will also cause high risk. In this research, we will develop a novel framework, which takes into account the market uncertainties and the risk attitude of generators in building optimal bidding strategies.

4.2 The proposed Framework of Optimal Bidding Strategy

4.2.1 Market Mechanism

A bid includes price offers and the amount of load to be satisfied by the market for each hour. The mechanism of a day-ahead electricity market is as follows Firstly, each generator uses a self-schedule algorithm to determine its optimal self-schedule. Secondly, each generator applies a bidding strategy to optimize its self-schedule in order to get maximum profit. Thirdly, the market participants submit their bids in trading intervals bids to a market. These bids are composed of a set of power prices and power offered in intervals. Finally, the market operator determines the generation and load dispatch, as well as the MCP via its economic dispatch algorithm, which select the cheapest available resource. The supplier that sets up the MCP is the most expensive one, and other suppliers are all paid at this price which is above their bids. Please note this mechanism is based on *System Marginal Price (*SMP) Auction, more details can be found in Chapter 2.

Generators' behaviour depends on several elements such as daily forecast demand and price, system availability, the predicted generation reserve, transfer between the regions, contract position and its degree of risk aversion under price uncertainties.

4.2.2 Self-scheduling

In self-scheduling, the profit maximization problem can be formulated as follows:

$$\max \sum_{t=1}^{T} (\lambda_{ti} * q_{ti} - C_{ti}) \tag{4.1}$$

Subject to: Ramp-up rate limits

Ramp-down rate limits

Start-up ramp rate limits

Shut-down ramp rate limit

where λ_{ti} represents the forecasted MCP at hour t and scenario i in \$/MWh and q_{ti} the power produced by the generator at hour t and scenario i in MW.

For simplicity, in the experiment, variable production cost C_{ti} will be used as the generator's operation cost neglecting the fixed, shut-down, and start-up cost in the function. These variables can be implemented in a similar way if needed. This objective function will be used to optimize a generator's bids with the forecast price as the λ_{ti} variable and then an optimization algorithm will be applied to solve this self-scheduling problem and get the optimal production of electricity.

4.2.3 Major Steps of the Proposed Framework

As discussed before, a major objective of our framework is to estimate and handle the uncertainties. To accomplish this goal, advanced data mining and statistical techniques will be integrated in the framework – see Fig 4-1. The major steps of the framework are as follows:

(1) Employing load and price forecasting techniques to forecast the future loads and prices

It is essential to accurately forecast the future loads and prices so that the generator can assure it will be dispatched. In the proposed framework, traditional time series methods (e.g. *Autoregressive Integrated Moving Average* (ARIMA)), machine learning techniques (Neural Networks or SVM) or Game Theory methods can be selected to estimate the future loads and prices. Comprehensive experiments had been conducted to determine which technique is superior in load and price forecasting.

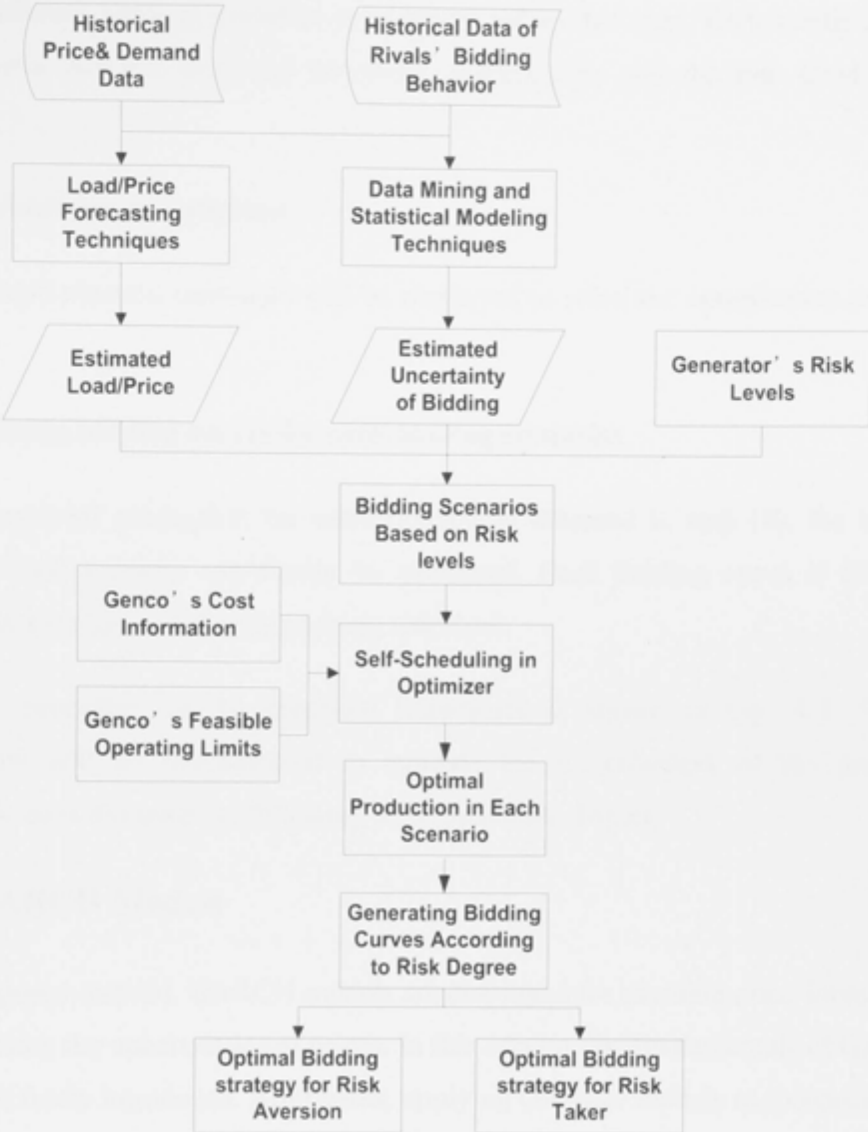

Figure 4-1 The Proposed Bidding Strategy Framework

(2) Employing data mining and statistical methods to quantify the market uncertainties

Significant uncertainties present in designing bidding strategies. The uncertainties come from many sources, such as the price volatility and the uncertainties of rivals' behaviours. A GARCH model and associated statistical methods will be developed to quantify the uncertainties so that based on the estimated uncertainties we can build different strategies according to the risk attitudes of generators.

(3) Building bidding scenarios

Several different bidding scenarios are constructed in this step. Each scenario has a bidding price derived from the estimated uncertainties and the risk level of the generator.

(4) Self-scheduling in optimizer

EC based optimization technique will be employed to solve the optimization problem in (4.1).

(5) Generating bidding curves for each bidding scenarios

After the optimal production for each scenario is obtained in step (4), the bidding curve for each scenario can finally be generated. Each bidding curve is designed specifically for a generator with a certain risk level.

The basic procedure of the proposed framework is shown in Fig. 4-1. Several experiments will be implemented to validate the effectiveness of the proposed framework, as is discussed in following sections in this chapter.

4.3 GARCH Models

In the proposed method, GARCH models are employed for accurate price forecasting, and estimating the uncertainties of prices. In this section, the fundamentals of GARCH models are firstly introduced. Afterwards, applying GARCH models to forecasting the conditional mean and variance of MCP is discussed; followed by the discussion on constructing several price scenarios with the outputs of GARCH models.

4.3.1 The Fundamentals of GARCH Methodology

In the traditional Box-Jenkins approach to time series analysis, time series models are usually assumed to follow these conditions [92]:

$$Y_t = c + \sum_{i=1}^{m} \phi_i Y_{t-i} + \varepsilon_t + \sum_{i=1}^{l} \theta_i \varepsilon_{t-i} \tag{4.2}$$

$$\varepsilon_t \sim N(0, \sigma^2) \tag{4.3}$$

$$E(\varepsilon_t \varepsilon_\tau) = 0 \quad \text{for } t \neq \tau \,, \tag{4.4}$$

where ε_t is Gaussian white noise [92] and uncorrelated across time. This model is known as the ARMA (m,l) (Autoregressive Moving Average) model. It assumes that the current observation of a time series is determined by the previous observations and Gaussian disturbances. Sometimes, Y_t may also be related to some explanatory variables. The ARMA model is then naturally generalized to the ARMAX model, which takes the form:

$$Y_t = c + \sum_{i=1}^{m} \phi_i Y_{t-i} + \varepsilon_t + \sum_{i=1}^{l} \theta_i \varepsilon_{t-i} + \sum_{i=1}^{k} \gamma_i X_i \tag{4.5}$$

where X_i represents the explanatory variable. Assuming the above models, the conditional distribution of Y_t can be shown to follow a Normal distribution [92]:

$$Y_t|_{t-1} \sim N(c + \sum_{i=1}^{m} \phi_i Y_{t-i} + \sum_{i=1}^{l} \theta_i \varepsilon_{t-i} + \sum_{i=1}^{k} \gamma_i X_i, \sigma^2) \tag{4.6}$$

The optimal forecast of Y_t is:

$$\hat{Y}_t = E(Y_t|_{t-1}) = c + \sum_{i=1}^{m} \phi_i Y_{t-i} + \sum_{i=1}^{l} \theta_i \varepsilon_{t-i} + \sum_{i=1}^{k} \gamma_i X_i \tag{4.7}$$

which theoretically leads to the minimum MSE (mean square error). The forecast (4.7) is therefore also referred to as the minimum MSE forecast.

The validity of the Box-Jenkins approach is strictly proven. Unfortunately, its assumption of constant variance is often violated in practice. In real-world applications, the variance of ε_t is usually time-changing or correlated with explanatory variables. Modelling the time-changing variance is essential in handling the time series with large volatility. An accurate estimate of the conditional variance can significantly improve the forecasting accuracy. Moreover, it is also useful for estimating the risk of forecasting, which will be discussed in the following sections. GARCH models are therefore introduced to solve this problem. It is usually expressed as [92]:

$$Y_t|_{t-1} \sim N(\vec{X}_t' \vec{B}, \sigma_t^2) \tag{4.8}$$

$$h_t = \sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i} + \sum_{i=1}^{p} \beta_i h_{t-i} \tag{4.9}$$

$$\varepsilon_t = Y_t - \vec{X}_t' \vec{B} \tag{4.10}$$

$$\vec{X}_t' = (1, Y_{t-1} \ldots, \varepsilon_{t-1} \ldots, X_i \ldots) \tag{4.11}$$

$$\vec{B}' = (c, \phi_i \ldots, \theta_i \ldots, \gamma_i \ldots) \tag{4.12}$$

Note that (4.8) is actually the same as (4.7). Therefore, model (4.8)-(4.12) can be viewed as an ARMAX model with the GARCH disturbance. It still uses the ARMAX model to estimate the conditional mean of Y_t, but introduces Equation (4.10) to handle the conditional variance. The model (4.8)-(4.12) is called an ARMAX (m,l,k) + GARCH (p,q) model. Note that the GARCH (p,q) model is a generalization of the *Autoregressive Conditional Heteroscadasticity (ARCH)* model. If we set $p=0$, the model will actually become the ARCH (q) model as introduced in [92].

Building a GARCH forecasting model usually includes the following steps:

(1) Test the GARCH effect with the Lagrange multiplier test to determine whether GARCH models are applicable;

(2) Identify a GARCH model with a proper form according to data;

(3) Estimate the parameters of the GARCH model;

(4) Validate model effectiveness. If the model is satisfactory, continue to step (5), otherwise, go back to step (2);

(5) Apply the GARCH model to forecast the test time series data.

4.3.2 Forecasting with GARCH Models

After a proper GARCH model is identified, it then can be used on the out-of-sample data to forecast the electricity price. The procedure of GARCH forecasting is illustrated in Figure 4-2. Different from ARIMA or machine learning techniques, a GARCH model can be used to forecast both the mean and variance of a time series. Given a sample of a time series $Y_1, Y_2, \ldots Y_{t-1}$ and its explanatory variables $\vec{X}_1, \vec{X}_2, \ldots \vec{X}_{t-1}$, the optimal forecast of Y_t given by the GARCH model is the same as that of ARMAX,

$$\hat{Y}_t = E(Y_t|_{t-1}) = c + \sum_{i=1}^{m} \phi_i Y_{t-i} + \sum_{i=1}^{l} \theta_i \varepsilon_{t-i} + \sum_{i=1}^{k} \gamma_i X_i . \tag{4.13}$$

In GARCH forecasting, this is called conditional mean forecasting [93], because it employs the conditional mean of Y_t as its forecast. Similar to ARMAX, (4.13) is still a minimum MSE forecast. Although the conditional mean forecast of GARCH has the same form as ARMAX, it can significantly outperform ARMAX because the conditional variance equation (4.13) is introduced.

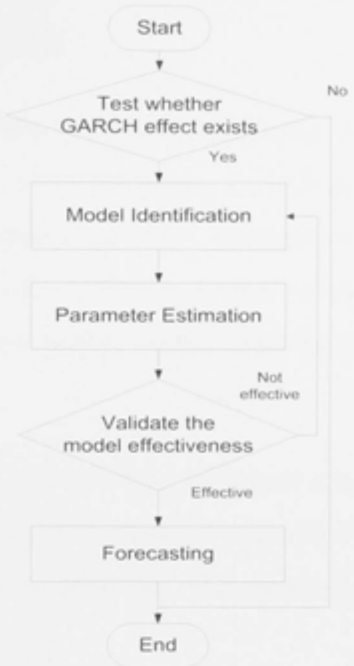

Figure 4-2 The Procedure of GARCH Forecasting

Besides enhancing the forecasting of Y_t, another major application of GARCH model is to perform conditional variance forecasting. According to [94], we have:

$$Var(Y_t|_{t-1}) = E(\varepsilon_t^2|_{t-1}) = \sigma_t^2 . \tag{4.14}$$

The *Minimum Square Error* (MSE) forecasting of the conditional variance of Y_t is therefore given as,

$$\hat{\sigma}_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i} + \sum_{i=1}^{p} \beta_i h_{t-i} . \tag{4.15}$$

The forecast of the conditional variance is essential for estimating the risk of forecasting. To control the forecasting risk, the standard statistical approach is to give the prediction interval [92, 95]. Generally speaking, an α level prediction interval of Y_t is a stochastic interval $[L_t, U_t]$, which satisfies:

$$P(Y_t \in [L_t, U_t]) = 1 - \alpha . \tag{4.16}$$

The implication of (4.16) is that Y_t will fall in $[L_t, U_t]$ with a probability of $1-\alpha$. With the prediction interval, the decision makers can conveniently control the decision risk by setting a proper α. GARCH models employ both the conditional mean forecast and conditional variance forecast to calculate the prediction interval, the detailed discussion about calculating the prediction interval with GARCH can be found in [92].

4.3.3 Constructing Price Scenarios

To consider the different preference of the risk averse and risk seeker, a possible solution is to construct several price scenarios. Several prices above and below the forecasted price will be calculated and the corresponding optimal production is obtained. The risk averse will choose one or several scenarios with the prices lower than the forecasted price. The risk seeker, on the other hand, will choose the scenarios with higher prices.

To construct price scenarios for a time t, the conditional mean forecast and conditional variance forecast given by the GARCH model is essential. For each price scenario, an upper-sided prediction interval is obtained. The upper-sided prediction interval is defined as:

$$P(Y_t \in [-\infty, U_t]) = \alpha \tag{4.17}$$

Here U_t will be the bidding price for the scenario with confidence level α`, and is calculated as:

$$U_t = \hat{Y}_t + z_{1-\alpha} \times \hat{\sigma}_t, \tag{4.18}$$

where $z_{1-\alpha}$ is the upper $1-\alpha$ critical point [93] of the standard normal distribution. Note that in (4.17), α represents the probability that the real price is lower than U_t; α therefore is an indicator of the risk of a scenario. A smaller α implies that the generator is more likely to be dispatched, and vice versa. The risk seeker would choose the scenarios with higher prices and greater α. The risk averse would prefer the smaller α and lower profits. For each scenario, α is useful for calculating the expected profit, which has considered the risk of prices. GA is used to find the optimal solution to this problem.

4.4 Case Studies

In this section, an empirical study is conducted to analyse the profit obtained with the proposed bidding strategy technique. The aim of this case study is to demonstrate how the bidding strategies can optimise the generator's profit.

It is assumed that a 294-MW coal-fired generator is located in the Australian NEM and is selected in these case studies. The individual operating constrains of the generator are based on the data of [96] Table 4-1 shows the individual operating constrains of the thermal plant.

Table 4-1 Operating Constraints of the Generator

Minimum power output [MW]	112
Maximum capacity[MW]	294
Start-up ramp rate limit[MW/h]	170
Shut-down ramp rate limit[MW/h]	160
Ramp-up rate limit[MW/h]	60
Ramp-down rate limit[MW/h]	50

The variable cost used in this chapter is linearized into 10 blocks and the slopes of each block are presented in Figure 4-3.

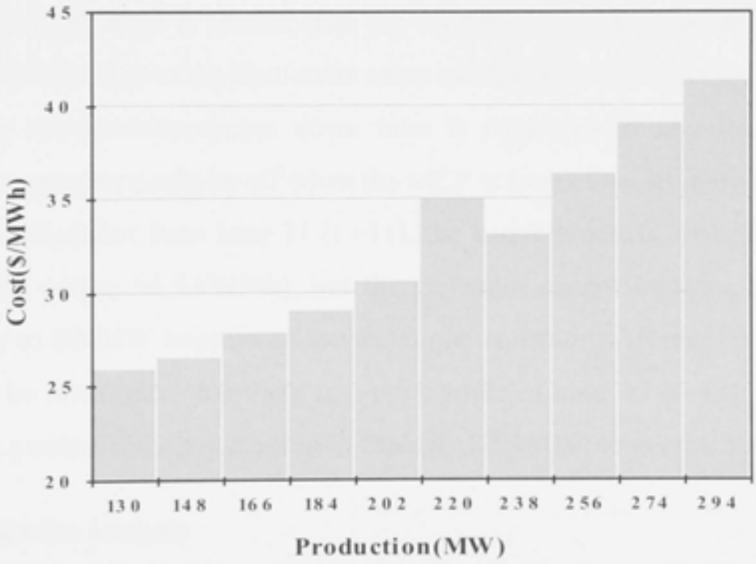

Figure 4-3 Piecewise Linear Variable Cost

The production of 170MW is taken as the initial state in self-scheduling. It is assumed that the system has been running in this production level for 11 hours. It is also assumed that the generator's production remains the same within each hour.

4.4.1 Self-scheduling

The self-scheduling could be performed by optimizing the objective function (4.1). Then the generator's optimal production can be calculated for the nine price scenarios with different confidence levels. The optimal production for bidding at the forecasted MCP is shown in Fig. 4-4.

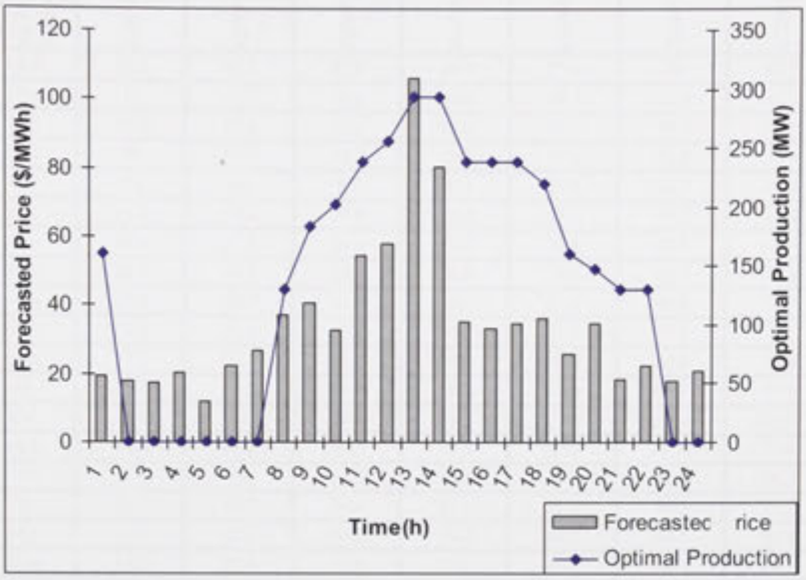

Figure 4-4 Optimal production of the generator for bidding at the Forecasted price

In hour 1 (t=1), the MCP is smaller than the variable cost and the generator's profit is negative. However, due to the shut-down ramp rate limit, the unit cannot be shut-down. Because the minimum/maximum down time is neglected in this study, after this interval, the generator could be off when the MCP is lower than its marginal cost slope. It should be noted that from hour 11 (t =11), the variable cost is lower than the MCP ($41.27/WMh versus 54.53/WMh), but the generator cannot increase its production immediately to 294MW because of the technique constraints (Ramp-up rate limit). It should also be mentioned that there is a price spike in hour 13 (t=13), the generator increases its production to the maximum capacity (294MW) to get the maximum profit.

4.4.2 Scenarios analysis

Based on the real price data of the Australia NEM on 13 Jan, 2005, the price scenarios and optimal production obtained from the self-scheduling are shown in Tables 4-2 and 4-3.

Table 4-2 Price Scenarios for the Case Study

Hour	Price[$/MWh]								
	Forecasted Price Value	2.50%	12.50%	25.00%	37.50%	62.50%	75.00%	87.50%	97.50%
1	19.4	12.1	15.1	16.9	18.2	20.6	22	23.8	26.8
2	17.6	11	13.7	15.4	16.6	18.7	19.9	21.5	24.3
3	17.3	11.4	13.8	15.3	16.4	18.3	19.4	20.8	23.3
4	20.5	14	16.7	18.3	19.5	21.6	22.8	24.4	27.1
5	11.7	3.1	6.6	8.7	10.3	13.1	14.7	16.8	20.4
6	22.2	15.2	18.1	19.8	21.1	23.4	24.7	26.4	29.3
7	26.9	19.9	22.8	24.5	25.8	28.1	29.3	31	33.9
8	36.9	23.7	29.2	32.4	34.8	39.1	41.5	44.7	50.2
9	40.8	23.8	30.8	34.9	38	43.5	46.6	50.7	57.7
10	32.9	19.2	24.9	28.2	30.7	35.2	37.7	41	46.7
11	54.5	27.5	38.7	45.2	50.1	58.9	63.8	70.4	81.5
12	58	25.3	38.8	46.8	52.7	63.4	69.3	77.3	90.8
13	106	32.8	63	80.8	94.1	117.9	131.1	148.9	179.1
14	80.1	13.8	41.2	57.3	69.3	90.9	102.9	119	146.4
15	35	3.4	5.4	17.6	26.8	43.2	52.3	64.5	85.3
16	33	5.1	10.7	19.9	26.8	39.2	46.1	55.3	71.1
17	34.5	5.7	17.6	24.5	29.8	39.1	44.4	51.4	63.3
18	36.4	13.8	23.2	28.6	32.7	40.1	44.2	49.7	59
19	25.8	8.6	15.7	19.9	23	28.6	31.8	35.9	43.1
20	34.6	18.9	25.4	29.2	32.1	37.2	40.1	43.9	50.4
21	18.3	4.9	10.5	13.7	16.1	20.5	22.9	26.2	31.7
22	22.5	12.1	16.4	18.9	20.8	24.2	26	28.6	32.8
23	17.7	9.6	12.9	14.9	16.4	19	20.5	22.5	25.8
24	20.8	16.6	18.3	19.3	20.1	21.4	22.2	23.2	25

Table 4-3 Optimal Production of Self-Schedule

Hour	Optimal Production [MW]								
	Fore. MCP	2.50%	12.50%	25.00%	37.50%	62.50%	75.00%	87.50%	97.50%
1	160	160	160	160	160	160	160	160	160
2	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	130	0
5	0	0	130	0	0	0	0	130	0
6	0	0	130	130	130	0	130	130	130
7	0	130	130	130	130	130	130	130	184
8	130	130	130	148	148	166	184	184	238
9	184	130	130	148	184	184	184	238	238
10	202	130	130	130	202	148	184	184	256
11	238	130	166	184	238	184	238	238	294
12	256	130	166	238	238	238	238	294	294
13	294	148	238	238	294	294	294	294	294
14	294	184	202	238	238	294	294	294	294
15	238	166	256	130	184	256	294	294	294
16	238	130	202	130	130	220	294	294	294
17	238	130	166	130	130	184	294	294	294
18	220	130	130	130	148	148	294	294	294
19	160	130	130	0	130	130	294	294	294
20	148	130	130	0	148	148	294	294	294
21	130	130	0	0	130	130	274	294	294
22	130	0	0	0	130	130	274	294	294
23	0	0	0	0	130	130	238	294	294
24	0	0	0	0	0	0	202	294	294

In order to show how generator's degree of risk aversion affects its profit, the optimal production and forecasted price for different confidence levels are employed to constitute the optimal bidding curves respectively for risk taker and risk aversion. In order to get the maximum profit, a risk taker usually bids at a price greater than the forecasted price. In other words, it usually chooses the scenarios with the confidence level α from 62.5% to 97.5%. On the contrary, a risk averse will offer at a price which is lower than the forecasted price and the confidence levels will be from 2.5% to 37.5%.

Four hours in twenty four intervals were selected to show the bidding curves of the risk taker and risk averse. Table 4-4 illustrates the scenarios for a risk taker and Table 4-5 shows the scenarios for a risk averse.

Table 4-4 Scenarios for a Risk Taker in Four Intervals

Hour	Scenarios (%)	Price [$/MWh]	Production [MW]
7	62.5	28.05	130
	75	29.32	130
	87.5	31.02	130
	97.5	33.9	184
12	62.5	63.36	238
	75	69.31	238
	87.5	77.26	294
	97.5	90.78	294
16	62.5	39.19	220
	75	46.1	294
	87.5	55.34	294
	97.5	71.06	294
21	62.5	20.5	130
	75	22.93	274
	87.5	26.18	294
	97.5	31.71	294

Table 4-5 Scenarios for a Risk Averse in Four Intervals

Hour	Scenarios (%)	Price [$/MWh]	Production [MW]
7	2.5	19.93	130
	12.5	22.82	130
	25	24.51	130
	37.5	25.78	130
12	2.5	25.29	130
	12.5	38.82	166
	25	46.77	238
	37.5	52.71	238
16	2.5	5.06	130
	12.5	10.66	202
	25	19.9	130
	37.5	26.81	130
21	2.5	4.94	130
	12.5	10.47	0
	25	13.72	0
	37.5	16.15	130

According to the market clearing mechanism, the generator's bidding prices are compared with real MCP to determine the final market dispatching. Only the blocks in which the bidding prices are lower than the real MCP will be dispatched. On the contrary, the generator will lose the opportunity to be dispatched if its prices are greater than the real MCP. Therefore, if the bidding strategies are based on the forecast MCP, the accuracy of the forecasting price can significantly influence the generator's profit. This is also the reason for applying GARCH models in the proposed methodology. Moreover, it has been proved that this method is effective in increasing the accuracy of price forecasting.

The real price in our case study is shown in Fig.4-5.

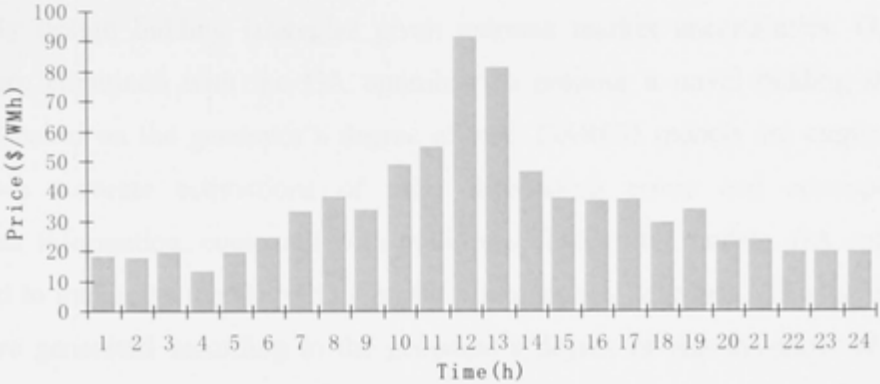

Figure 4-5 Real MCP for 13 Jan, 2005

The profit in each interval can be calculated by using equation (4.1) according to the real MCP after the real dispatch. The consequent profit for the risk taker and risk averse, which bid the constructed bidding curves based on different scenarios, are \$11,296 and \$21,318 respectively. Obviously, by taking the proposed bidding strategy, a risk averse can get more profits. As mentioned above, if the generator shows no preference for risk taking or reversion then the profit is based on the offers bidding at the forecasted MCP.

Notice that because the thermal unit in this case study has technical constraints; in order to make profits from price spikes, they will lose some profit in the intervals before spikes, especially when the price is fluctuating.

Another interesting result found in this study is that whether to take risk is sometimes decided by the market share of the generator. In a fully competitive market, participants intend to bid at their marginal costs. Unfortunately, the electricity market is more like an oligopoly market in which only a few generators participate in competition. Some participants will act as price-setters in the market competition, while other smaller generators will act as price takers. For the price-setter therefore, it will be more feasible for them to take the risk to make more profits since they could bid at a high price and still be dispatched. On the contrary, a price-taker should choose to avoid the risk, because if it bids a high price which is higher than the real MCP, it will probably lose the opportunity to be dispatched and finally decrease its profit.

4.5 Conclusions

In this chapter, a novel framework is proposed, which can be used to build optimal bidding strategies under highly uncertain market conditions. A variety of forecasting, data analysis and optimization techniques can be incorporated into this framework to effectively design bidding strategies given extreme market uncertainties. GARCH models are combined with the GA optimizer to propose a novel bidding strategy approach based on the generator's degree of risk. GARCH models are employed to give more accurate estimations of price forecasting errors and corresponding confidence information, compared with traditional forecasting models. GA optimizer is applied to maximize the GENCO's profit during its self-schedule. Finally, bidding curves are generated according to the generator's degree of risk aversion. With the proposed approach, once forecasted prices are available, the generator's self-scheduling problem can be formulated without the further consideration of other competitors, i.e. the optimal bidding curves can be obtained independently of the problems of other rivals. Simulations are conducted based on real market prices. Detailed discussion is given to demonstrate the effectiveness of the proposed method.

It is worth noting that the proposed approach depends on forecast prices using current historical prices to help the decision making process. Given the complexity of the market prices, in order to properly accounting for the impact of forecast prices on current prices, the forecast modules need to be continuously updated through a number of means such as back casting.

In view of market conditions, in addition to uncertainties in the market, incomplete information from market participants is another key feature and result of deregulation. Often, generators will have to build their bidding strategies based on incomplete market information. The capability of handling such incomplete information whilst achieving the best outcome is a challenging task for generators in the volatile market. In the following chapter, further enhancement of this framework will be presented. The new features and functionalities enable the framework to be used with confidence to generate optimal bidding strategies in a market with incomplete information.

Chapter 5

Developing Generators' Strategic Bidding in an Electricity Market Adding Rival Generators' Information Estimation

In the previous chapters, fundamentals of generator bidding and a general framework of bidding strategy modelling have been presented. The proposed general framework addressed a common problem in an electricity market, i.e. uncertainty. Techniques are also presented to handle such uncertainties effectively. In this chapter, the research is advanced by new methodologies to add rival generators incomplete information in a market in order to form bidding strategies for a generator. This is achieved by *Support Vector Machine* (SVM) and DE based approach as to be detailed in the sequel.

5.1 Introduction

In this section, the problem of bidding decision-making is studied from the viewpoint of a GENCO. A non-linear relationship between generators' bidding productions and MCP is estimated. A new method is proposed in this section to add rival generators incomplete information to build optimal bidding strategies. This method is based on SVM [97] with a DE bidding strategy optimizer and Monte Carlo simulation technique. SVM is an advanced technique that has attracted extensive research in data mining and has been successfully applied in electricity price forecasting [98]. It has been proven to be effective in estimating the non-linear functional relationship, hence is employed in the proposed method to estimate the relationship between MCP and generators' bid productions.

It is assumed that the bidding production of a generator in each dispatch interval follows a normal distribution. The parameters of these normal distributions can be estimated from historical bidding data. After having obtained the probability density function (PDF) and its parameters (mean and standard deviation), SVM is employed to estimate the non-linear relationship between bidding productions and MCP from publicly available historical market data. To deal with the problem of inherent stochastic structures, the Monte Carlo simulation is applied to acquire approximate solutions by performing statistical sampling experiments. In each iteration of the Monte Carlo simulation, the outcomes of SVM are used in a bidding strategy optimizer based on DE to maximize GENCO's profit during its self-schedule and then provide the optimal strategies comprising price-production pairs. By estimating the price distribution from historical price data, the proposed method is able to construct a series of price scenarios according to generators' different attitudes to risk. The proposed method is therefore useful for both the risk averse and risk taker.

The main contributions of this methodology are as follows:

- ***Prediction of Rivals' Behaviours***

By employing an advanced data mining technique, rivals' behaviours can be accurately predicted based on publicly available market data. This method therefore effectively solves the incomplete information problem commonly existing in an electricity market.

- ***Handling Uncertainties***

The Monte Carlo simulation and statistical estimation techniques are used to reliably handle the uncertainties involved in designing the optimal bidding strategy.

5.2 Problem Formulation

In the proposed bidding strategy model, suppose that there are n independent generators and a group of loads. Each generator submits its bid of a price and production pair in each trading interval to ISO. A non-linear relationship is assumed between the generators' bidding productions and the MCP. It is also assumed that in each trading interval, the production of each generator obeys the normal distribution. The mean value μ_{ti} and standard deviation σ_{ti} can be estimated from historical bidding data. For each generator, there are technical constraints of output P_{imin} and P_{imax}, $1 \le i \le n$. The estimated MCP λ_t at trading interval t in \$/MWh can be calculated by:

$$\lambda_t = f\left[p_{t1}, p_{t2}, \cdots, p_{tn}\right] \quad 1 \le t \le T \tag{5.1}$$

where $p_{ti} \sim N\left(\mu_{ti}, \cdots, \sigma_{ti}^2\right)$ is the bidding productions of generator i at trading interval t in MW, T is the number of trading intervals in a day. In NEM, there are 288 trading intervals in a trading day. T is therefore set as 288 in this chapter. λ_t is estimated by SVM, which will be discussed in more detail in the next section.

The profit maximization problem can be formulated as follows:

$$
\begin{aligned}
\text{maximize} \quad & \sum_{t=1}^{T} \alpha\left[\lambda_t p_{ti} - C_{ti}(p_{ti})\right] \\
\text{subject to} \quad & \lambda_t = \mu_\lambda(t) + z_{1-\alpha}\sigma_\lambda(t) \\
& \mu_\lambda(t) = f(p_{t1}, p_{t2}, \cdots, p_{tn}) \\
& P_{i\min} v(t) \le p_{it} \le P_{i\max}\left[v(t) - z(t+1)\right] + z(t+1)SD \\
& -RDv(t-1) - SDz(t) \le p_t - p_{t-1} \le RUv(t-1) + SUy(t) \\
& y(t) - z(t) = v(t) - v(t-1) \\
& y(t) + z(t) \le 1 \\
& z(t) \in \{0,1\}
\end{aligned}
\tag{5.2}
$$

where α is the confidence level decided by the generator to adjust the MCP to take into account the risk attitude of the generator, $C_{ti}(p_{ti})$ is the cost of the ith generator to generate p_{ti} amount of power at time t, $\mu_\lambda(t)$ is the mean of MCP at time t, $\sigma_\lambda(t)$ is the variance of historical price data, $z_{1-\alpha}$ is the one-sided 1- α critical value of the standard normal distribution, $P_{i\min}$ and $P_{i\max}$ are the minimum and maximum power output of generator i in MW, $y(t)$, $z(t)$, $v(t)$ are the running, start-up and shut-down status changes, and SD, SU, SD and RD are shut-down ramp, start-up ramp, ramp-down, and ramp-up rate limit in MW/h. λ_t is the price at time t, $\mu_\lambda(t)$ is the mean value of the price and $z(t)$ is real number in between 0 and 1.

Based on the assumption that MCP is normally distributed (this can be seen from the price distribution from the Australian NEM data), it can be guaranteed that the real MCP will be greater than λ_t with a probability of α. Therefore, bidding at λ_t will have a probability of α to be dispatched. Generators can determine their risks by selecting different α. α >0.5 represents a risk averse; otherwise the generator is a risk taker.

In the optimization, the variable production cost will be used as the generator's operational cost, but for simplicity, fixed, shut-down, and start-up costs in the cost function are not considered at this stage. It should be noted that these parameters can be included easily similar to that of the operational cost. This objective function will be used in the chapter to optimize generator's bids with the MCP obtained from SVM as the λ_t variable and then DE will be applied as the optimiser for solving the self-scheduling problem and obtain the optimal electricity production.

5.3 Proposed Methodologies

5.3.1 Outline of the Proposed Method

In this section, a detailed description is given to the proposed method. As discussed in the preceding section, it is essential to estimate the function $f(\cdot)$ and parameters μ_{ti} and σ_{ti} before the optimization can be performed. These estimates can be obtained with SVM and standard statistical methods. After that, the Monte Carlo simulation is conducted. In each iteration of the Monte Carlo simulation, rival generators' productions p_{ti} at time t are randomly generated with the estimated density distributions. These productions can then be employed by SVM to give the predicted MCP at time t. DE is used to solve the optimization problem and obtain the optimal production at time t.

Given a training production data p_{ti}^{d} which is the production of generator i at time t, day d. D is the total number of days of the training data. The production distribution parameters of generator i can then be estimated as:

$$\mu_{ti} = \sum_{d=1}^{D} p_{ti}^{d} \Big/ D \tag{5.3}$$

$$\sigma_{ti} = \sqrt{\sum_{d=1}^{D} \left(\mu_{ti} - p_{ti}^{d}\right)^2 \Big/ (D-1)} \tag{5.4}$$

The second step of the proposed method is estimating $f(\cdot)$ with SVM. For each time point t, both the historical MCP λ_t and all generators' productions p_{ti} are available. In SVM training, p_{ti} are predictor variables (inputs), and λ_t is selected as the response variable (output). The relationship between λ_t and p_{ti} can be accurately estimated because SVM can approximate any nonlinear functional relationship.

After estimating $f(\cdot)$, μ_{ti}, and σ_{ti}, the Monte Carlo simulation and DE can be employed to solve the problem of designing the optimal bidding strategies. The Monte Carlo simulation is applied to obtain the optimal bids by performing random experiments. In each iteration of the Monte Carlo simulation, the outcomes of SVM are used in a DE based bidding strategy optimizer to maximize the GENCO's profit during its self-schedule and then provide the optimal strategies. By estimating the price distribution from historical price data, the proposed method is able to construct a series of price scenarios according to generators' different attitudes to risks. The proposed method is therefore useful for both the risk aversion and risk taker. More details about the Monte

Carlo method and DE are given in the following sections.

The flowchart of the proposed bidding strategy method is illustrated in Figure 5-1.

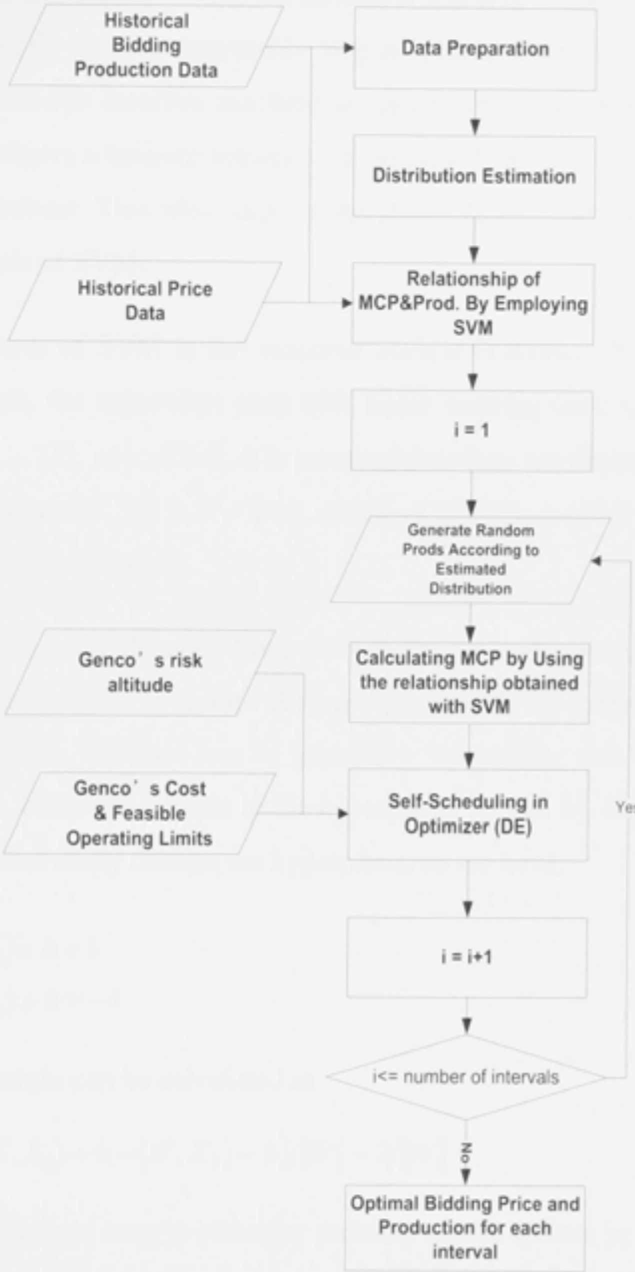

Figure 5-1 Flow Chart of the Proposed Bidding Strategy Method

5.3.2 *Support Vector Machine* (SVM)

SVM will be used as an estimating model in the experiments. A brief introduction to SVM is given for completeness.

SVM is a machine learning method proposed by Vladimir Vapnik et al. at Bell

Laboratories [99]. This method received increasing attention in recent years because of its excellent performance in both classification and regression. Generally, the SVM method is based on Vapnik's work on statistical learning theory [99]. Unlike previous regression methods such as regression tree or neural networks which minimize the empirical risk for the learning machine so as to achieve high forecasting accuracy, SVM tries to achieve a balance between the empirical risk and the learning capacity of the learning machine. This idea leads to the principle of structural risk minimization, which is the basis of SVM.

The simplest form of SVM is the *maximal margin classifier*. It is used to solve the simplest problem, the regression case with linear training data. Consider the training data $\{(X_1, y_1), \ldots, (X_l, y_l)\} \subset R^n \times R$, it is assumed that they are linear. It means that there exists a hyperplane $<W, X> + b = 0$ on which $y_i(<W, X_i> + b) > 0$ where $<W, X>$ is the dot product between W and X.

Margin is defined as the distance from the hyperplane to the nearest point. The aim of maximal margin classifier is to find the hyperplane with the largest margin, named as maximal hyperplane. Without loss of generality, we assume that the two points with label +1 and –1, which are nearest to the hyperplane, X_1 and X_2. Note that the rescaling of W and b will not really change the hyperplane, so we have:

$$\begin{aligned} \langle W, X_1 \rangle + b &= 1 \\ \langle W, X_2 \rangle + b &= -1 \end{aligned} \qquad (5.1)$$

The maximal margin can be calculated as:

$$r = \left(\langle W, X_1 \rangle + b - \langle W, X_2 \rangle - b\right) / \|W\| = 2/\|W\| \qquad (5.1)$$

Therefore, the maximal margin classifier problem can be written in the following form:

$$\begin{aligned} &\text{minimize} \quad \|W\|^2/2 \\ &\text{subject to } y_i\left(\langle W, X_i \rangle + b\right) \geq 1 \quad 1 \leq i \leq l \end{aligned} \qquad (5.2)$$

The Lagrange multipliers method can be used to solve this optimization problem of (5.3).

In most real-world problems, the training data are not linearly separable. There are two methods to modify linear SVM to suit the non-linear case. The first is to introduce some slack variables to tolerate some training errors to decrease the influence of the noise in the training data. Another method to deal with non-linear data is to use a map function $\Phi(X)$: $R^n \rightarrow H$ to map the training data from input space into some high dimensional feature space, so that they will become linearly separable in the feature space. Then SVM can be applied in the feature space. Note that the training data used in SVM are only in the form of dot product, therefore, after the mapping the SVM algorithm will only depend on the dot product of $\Phi(X)$. If we can find a function that can be written in the form of $K(X_1, X_2) = \langle\Phi(X_1), \Phi(X_2)\rangle$, the mapping function $\Phi(X)$ will not need to be explicitly calculated in the algorithm. $K(X_1, X_2)$ is a *kernel function* or *kernel*.

Radial basis kernel is used in this chapter:

$$K(X,Y) = e^{-\|X-Y\|^2/(2\sigma^2)} \tag{5.3}$$

5.3.3 Monte Carlo Simulation to Obtain the Optimal Bidding Strategies

Monte Carlo simulation solves the stochastic optimization problem by performing statistical sampling experiments [97]. Before the Monte Carlo simulation, rival generators' bidding productions are assumed to follow normal distributions. In each iteration of the Monte Carlo simulation, rivals' bidding productions are randomly generated based on the estimated distribution. Considering the random productions as fixed numbers, building the optimal bidding strategy for the *i*th generator becomes a one-parameter search problem for which the bids from the other suppliers are fixed through the random sampling procedure. DE can then be applied to solve the deterministic optimization problem and obtain a bidding strategy. After a number of iterations, the mean values of bidding production and price, which are obtained at each iteration, will be selected as the optimal bid.

5.4 Case study

5.4.1 Problem Description

A detailed case study is performed based on a power system consisting of eleven thermal units with quadratic production costs and generation technical limits. There are three major objectives for this case study.

(1) To validate whether the proposed method can properly estimate rival generators' productions;

(2) In the experiments, the MCPs are obtained with SVM based on the random samples of estimated bidding production distribution. The profits obtained using the proposed method is compared with the real profits of each generator obtained from real market data, to demonstrate the effectiveness of the proposed method.

(3) The bidding results according to different risk levels α are presented and evaluate how the risk levels, which depends on the risk attitude of generators, will influence the bidding strategies are studied.

Till now, the NEM has been operating reliably and efficiently for over 10 years since December 1998. The *Australian Energy Market Operator* (AEMO) administrates and operates a competitive wholesale electricity market where supplies more than $10 billion electricity annually to meet the demand of more than 8 million end users. NEM is thus a good choice to be chosen for case studies. The case study is conducted based on the real market bidding production data of the Australian NEM from September 17 to October 16, 2006. Historical bidding data of the NEM are publicly available in the following trading day and are rather extensive, including all bids submitted, the unit that submitted the bid and the economic entity that controls the unit.

Eleven major generators located in the NEM are selected in the case study. Their capacities and technical constraints can be found in [15]. It is assumed in the case study that one of the 11 generators designs its bidding strategy with the proposed method, while other generators' bidding strategies are identical to the real bidding data.

5.4.2 Result Analysis

Figures 5-2 ~ 5-4 show the generators' real bidding productions and the estimated bidding productions obtained with the proposed method. From Figures 5-2 – 5-4, it is evident that the proposed method can accurately estimate rival generators' behaviours.

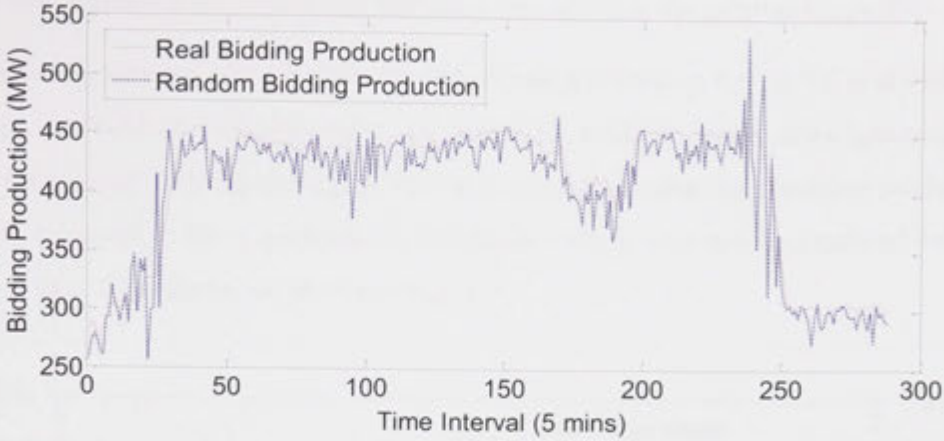

Figure 5-2 The Real Bidding Production vs Random Bidding Production of Generator 1

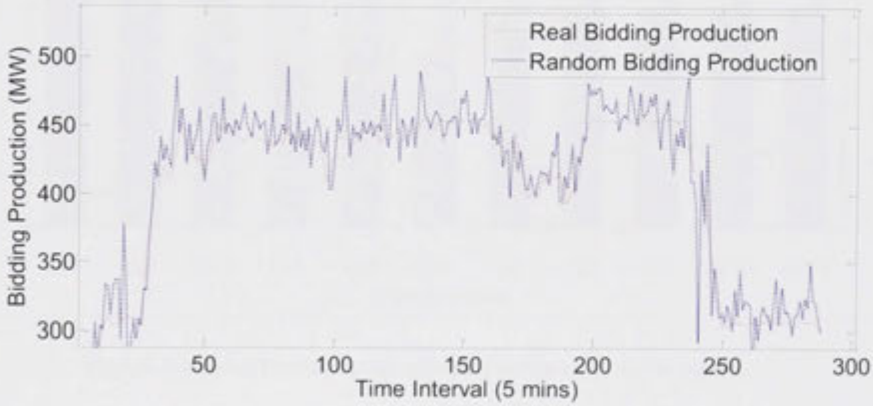

Figure 5-3 The Real Bidding Production vs Random Bidding Production of Generator 2

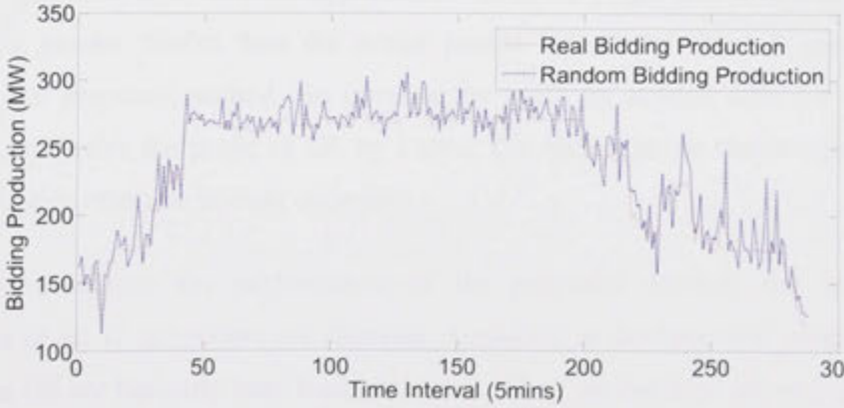

Figure 5-4 The Real Bidding Production vs Random Bidding Production of Generator 3

To analyse the profit obtained with the proposed bidding strategy technique, an empirical case study is conducted to compare the difference between the real profits and the profits obtained with the proposed method. The results of this study can be used to demonstrate how the bidding strategies can optimise the generator's profit.

The case study consists of 11 rounds. In each round, generator i, $1 \leq i \leq 11$, is assumed to design its bidding strategies with the proposed method, while other generators follow their actual bidding strategies. For each generator using the proposed method, its profit achieved in the experiment is compared with its real profit calculated from historical data. The results are shown in Fig. 5-5.

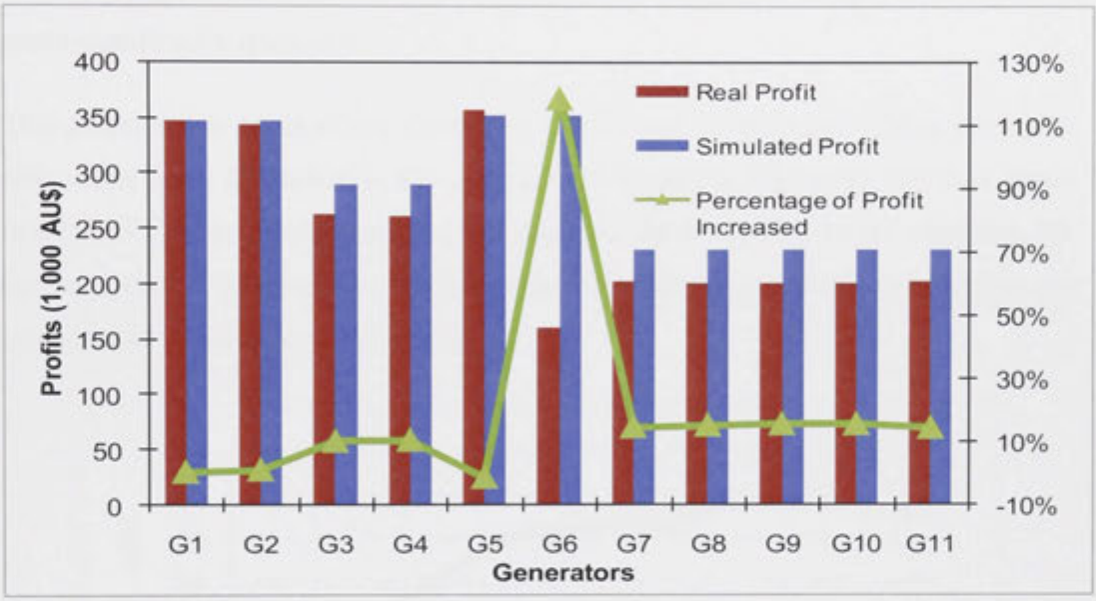

Figure 5-5 Real Profits vs Simulated Profits of 11 Generators

As clearly illustrated in Fig. 5-5, the profits obtained with our method are similar to the real profits for generators G1, G2 and G5. However, the proposed method results in significantly greater profits than the actual profits for all the other 8 generators. Moreover, the proposed method can increase the profit by at least 10% for these 8 generators, and raise the profit of G6 by 120%. The results prove that the proposed method is highly effective in most occasions.

To further investigate the performance of the proposed method, the historical productions of all 11 generators are checked. According to the historical productions, G1, G2 and G5 are basically base-load generators. Their productions are very close to their maximum capacities at most occasions. The proposed method cannot further increase their productions and therefore cannot significantly improve the profits. On the other hand, other 8 generators' productions are usually far from their maximum capacities. The proposed method can thus perform well.

As discussed in Section 2, the proposed method is applicable to both risk averse and risk taker, by selecting suitable confidence level α. To study the influence of α on the profit, the profits of generator G1 as obtained with the proposed method with respect to different α are plotted in Fig. 5-6. Clearly, the profit is increased when α is decreased from 90% to 70%. A large α indicates that the generator tends to bid at a low price to make sure it will be dispatched. However, bidding at a low price may decrease the MCP and thus decrease the generator's own profit, especially for a generator with relatively large market share. On the contrary, when α decreases from 70% to 10%, the profit significantly decreases.

This phenomenon implies that, although a small α can increase the bidding price, the risk of not being dispatched is also significantly increased. The profit therefore drops dramatically. In summary, a neutral risk level should be usually set for obtaining the optimal profit. Choosing an α which is either too large or too small, can degrade the performance of the proposed method.

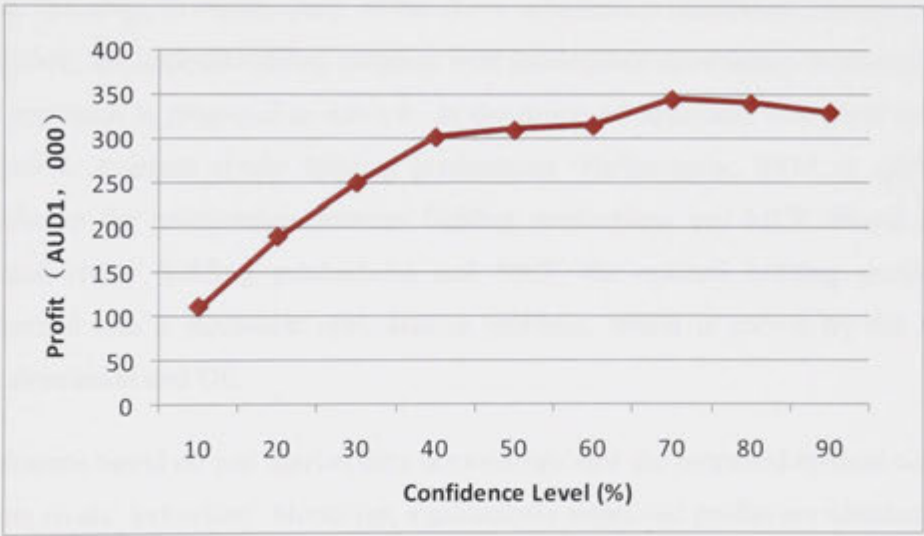

Figure 5-6 Profits of Generator G1 by Setting Different Confidence Level

The bidding prices and productions for generator G1, in four time intervals, are listed in Table 5-1. Notice that the thermal unit in the case study has technical constraints. In order to make profits from high price intervals, they will lose some profit in the intervals before the high price, especially when the price is fluctuating.

Table 5-1 Scenarios for Generator 1 in Four Intervals

Time→	6am		10am		4pm		8pm	
Confidence (%)↓	Price ($/MWh)	Production (MW)	Price ($/MWh)	Production (MW)	Price ($/MWh)	Production (MW)	Price ($/MWh)	Production (MW)
10	25.33	263	39.67	420	36.68	420	22.57	420
20	24.45	186	39.14	420	36.35	420	19.97	420
30	23.81	186	38.76	340	36.12	420	18.1	391
40	23.27	186	38.43	340	35.92	314	16.5	196
60	22.25	186	37.82	340	35.54	186	13.5	186
70	21.71	186	37.5	340	35.34	289	11.9	0
80	21.07	186	37.11	237	35.1	186	10.03	0
90	20.19	186	36.58	186	34.78	186	7.43	186

5.5 Conclusions

Designing optimal bidding strategies is a challenging task for generators in the deregulated electricity market. Existing methods usually assume that the rivals' information, such as cost information, bidding parameters and benefit functions, is known. However, in reality, most of the above information is business confidential. In this section, the optimal bidding problem with incomplete information is studied and a novel approach is proposed to solve it. In the proposed approach, statistical methods are used to estimate rivals' bidding productions. Furthermore, SVM is applied to approximate the relationship between bidding productions and MCP. Based on the estimated rivals' bidding productions and MCP, the optimal bidding problem is transformed into a stochastic optimization problem, which is solved by the Monte Carlo simulation and DE.

Experiments based on real market data demonstrate that the proposed method can well estimate rivals' behaviour. Moreover, significantly improved profits are obtained with the proposed method in the experiment. The proposed method is therefore proven effective in designing the optimal bidding strategies without knowing rivals' confidential information. Findings from this chapter provide a very useful tool for a generator strategic bidding in a market environment.

This chapter, together with the previous chapters form a rather complete framework for generation strategic bidding. However, as discussed in Chapter 1, in addition to energy sales in the spot market through bidding, generators also get their revenue from financial market using different financial instruments. The overall profitability of a generator depends on its overall portfolio management plans. In the next chapter, developed methodologies for optimal portfolio selection will be presented to form a rather comprehensive tool package for a GENCO to achieve risk management purpose and optimal risk-return trade-off.

Chapter 6

Optimal Portfolio Selection for Generators in an Electricity Market

6.1 Introduction

A competitive electricity market essentially consists of the day-ahead energy market, real-time energy market and ancillary services market. In a deregulated environment therefore, GENCOs are facing the problem of optimally allocating their generation capacities to different markets for profit maximization. Moreover, the generators have greater risks than before because of the significant price volatility in the spot energy market introduced by deregulation. To hedge the risks, generators can select a number of financial instruments available in the electricity market, such as forward and futures contracts [100-102]. All the above issues can be considered as a portfolio selection problem, which aims at maximizing the return and minimizing the risk of a generator by allocating the generator's assets to different markets and financial contracts. The portfolio selection problem essentially consists of two sub-problems. The first sub-problem concerns designing bidding strategies for the generator. This problem has been extensively studied in literature [5-7, 103]. Due to the deregulation and correspondingly greater market risks, it is important for generators to minimize risk by risk management, which is the second sub-problem of generators' portfolio selection. Comprehensive studies have been conducted on risk management for generators. The financial instruments available in the electricity market are studied in [104-107]. The risk management strategies for generators are discussed in [21, 108-111]. Moreover, the problem of allocating the capacities between the spot market and financial market also has attracted significant attentions [100-102].

There are two major challenges for constructing the optimal portfolio for a generator:

(1) Generators' portfolio selection consists of many issues with different characteristics, such as allocating the capacities among different markets and using a variety of financial contracts to hedge risk. It is therefore difficult to

develop a unified model for different markets and contracts. For example, the capacity allocation between the spot market and forward contracts is usually determined several months in advance. So in the long-term planning horizon, how to integrate the problem of optimal bidding strategies in a spot market with the problem of designing forward contracts for the generators is a big challenge.

(2) The selected portfolio is optimal only in the theoretical sense. Its performance largely depends on accurately estimating the probability distributions of the returns of different markets and contracts. However, these distributions are difficult to estimate, due to the greater price uncertainties in the deregulated market and the drawbacks of existing estimation techniques. The performances of existing portfolio selection approaches are therefore constrained.

In this chapter, a portfolio selection approach is proposed for GENCOs to allocating its generation capacities in different markets and using contracts for risk management. The proposed approach addresses all the issues of portfolio selection in a unified framework based on the Markowitz portfolio selection model [112, 113]. This approach selects the optimal portfolio by optimizing a utility function, which is a combination of the portfolio return and risk. The means and variances of different asset returns are derived separately. Considering that the electricity price is a heteroscedastic time series [93, 114], a time varying volatility time series model is introduced to properly model the spot price and estimate the price uncertainties. In this chapter, this approach is employed in the long term planning (several months ahead) and has well solved the problem of allocating generation capacities between spot market and forward contracts. Theoretically, the proposed approach can also be employed to solve the short term portfolio selection problem (day ahead), which deals with hedging price risks with standardized financial instruments, such as futures contracts. In summary, the proposed approach is applicable for handling different available assets in the electricity market. Moreover, it is able to provide better estimates of the distributions of asset returns by employing advanced statistical and econometrics methods. It therefore well addresses the challenges discussed above.

The rest of the chapter is organized as: The fundamentals of portfolio selection theory are discussed in Section 2. In Section 3, a time varying volatility model is firstly introduced to model the spot market price. Afterwards, the problems of long term and short term portfolio selection are discussed in detail. DE is then introduced as the optimizer in the proposed approach. In Section 4, case studies are conducted with real-world market data. Promising results are obtained to prove that the proposed method is effective. Section 5 finally concludes the chapter.

6.2 Portfolio Selection Theory

The proposed approach is based on the portfolio selection theory. Generally speaking, portfolio selection involves determining a combination of assets to achieve the best risk-return trade-off. In finance, asset is meant as probable future economic benefits controlled by an entity as a result of past transactions or events, and from which future economic benefits may be obtained [112]. For a GENCO, a number of different assets are available for constructing a portfolio. For instance, an asset for a generator can be the electricity sold through the spot market, the electricity sold through forward contracts, or futures for risk hedging. Therefore, the capacity allocation and risk management of GENCOs can be modelled together as a portfolio selection problem.

The goodness of an asset is evaluated by two criteria, *expected return* and *risk*. Since holding an asset is for obtaining the future benefits, its return is usually uncertain. Therefore, only its expected return can be calculated from a statistical sense. Moreover, since the return of an asset is uncertain, the asset holder will have the possibility of obtaining a return lower than the expected level. This possibility is the risk of the asset. Investors generally prefer the asset with higher return and lower risk. In practice however, the two goals usually cannot be achieved simultaneously. Therefore, trade-off between the return and risk should be achieved. The process of achieving this trade-off is the portfolio selection, [21].

In portfolio selection, the return of an asset is usually modelled as a random variable. The mean of the random variable is then considered as the *expected return* of the asset, while the variance represents the *risk*. Assume that there are m assets available. Denote the return of asset i as r_i, and the mean and variance of r_i as μ_i and σ_i^2 respectively. Then the return of the portfolio with m assets can be expressed as the weighted sum of the m variables:

$$r = \sum_{i=1}^{m} w_i r_i \tag{6.1}$$

The mean and variance of the portfolio can be easily given as [93, 114]:

$$\mu = \sum_{i=1}^{m} w_i \mu_i \tag{6.2}$$

$$\sigma^2 = \sum_{i=1}^{m} \sum_{j=1}^{m} w_i w_j \operatorname{cov}(r_i, r_j) \tag{6.3}$$

where $\operatorname{cov}(r_i, r_j)$ is the covariance between r_i and r_j. It represents the correlation between the returns of asset *i* and *j*.

Since a higher return usually leads to a greater risk, a utility function is usually employed as the optimization objective to achieve a proper trade-off [112]:

$$U = \mu - 0.005 \times A \times \sigma^2 \tag{6.4}$$

In (6.4), A is the *risk aversion* degree of the investor, which is the generator in this case. Objective (6.4) implies that, the utility of a portfolio is enhanced by high expected returns and diminished by high risk. Moreover, the risk aversion degree also has vital impact on the risk return trade-off. This parameter is determined by the investor itself, and usually can be estimated by conducting risk questionnaires [112].

In summary, given a set of assets, portfolio selection aims at selecting appropriate weights w_i to optimize objective (6.4). This problem can be solved with a number of optimization techniques, such as DE [76]. The problem remaining is how to estimate the means, variances and covariances of the assets available to the generator. This problem is addressed in the following sections.

6.3 Portfolio Selection for GENCOs

In this section, we discuss the details of the proposed approach of selecting optimal portfolio for generators. We will address three major problems in applying portfolio selection theory in the electricity market:

- How to model the spot market electricity price, which is the main cause of risks for generators.
- How to obtain accurate estimates of the return parameters.
- How to apply the portfolio selection theory for different planning horizons.

6.3.1 Modelling the Spot Market Electricity Price

A major way for a generator to sell its power is through the spot energy market. Therefore, the spot electricity price has significant impact on generators' profits. Moreover, it can also influence the prices of other financial instruments, such as futures and option contracts. Therefore, it is a major risk source for generators. It is important to properly model the spot price so as to derive the distribution parameters of different assets.

The electricity price in the spot market is highly volatile and difficult to forecast. It is widely accepted to be a non-stationary and heteroscedastic time series [93, 114], which means that it has time varying mean and variance. Therefore, we cannot directly calculate the mean and variance of the return of the spot market, since they are not fixed. Instead, a time varying volatility model is introduced in this chapter to appropriately model the spot price:

$$Y_t = \sum_{i=1}^{p} \lambda_i Y_{t-i} + \sum_{j=1}^{l} \varsigma_j X_{t,j} + \sum_{k=1}^{q} \Phi_k \varepsilon_{t-k} + \varepsilon_t \tag{6.5}$$

$$\varepsilon_t = \sigma_t \cdot v_t \tag{6.6}$$

$$v_t \sim \mathrm{N}(0,1) \tag{6.7}$$

$$\vec{X}_t^{'} = (X_{t,1}, X_{t,2}, \ldots, X_{t,J}) \tag{6.8}$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{S} \alpha_s \varepsilon_{t-S}^2 + \sum_{j=1}^{l} \beta_j X_{t,j} \tag{6.9}$$

where

Y_t is the spot electricity price at time t;

$\vec{X}_t^{'}$ is the explanatory variables vector at time t;

ε_t is the noise at time t;

σ_t is the standard deviation of the electricity price at time t;

σ_t^2 is the variance of the electricity price at time t.

In model (6.5)-(6.9), the spot price is represented by a random variable Y_t. $\vec{X}_t^{'}$ is the vector that consists of all explanatory variables relevant to the price, such as market demand and supply. ε_t is the random noise that cannot be forecasted. The implication of this model is that, the spot price Y_t is a function of its predecessors $Y_{t-1...}$, the previous noises $\varepsilon_{t-1...}$, and the explanatory variables $\vec{X}_t^{'}$. Moreover, the variance of the electricity price σ_t^2 is also determined by the previous noises and the explanatory variables. Therefore, the variance is time changing and the model is a time varying volatility model. This model is introduced to suit the characteristics of the electricity price. We will demonstrate that the electricity price can be reduced with time varying volatility in the following sections.

In model (6.5)-(6.9), $\lambda, \varsigma, \phi, \alpha, \beta$ are parameters that should be estimated from historical data. In this chapter, the *Maximum Likelihood Estimation (MLE)* [115] is employed to obtain the parameter estimates. We introduce the following theorem:

Theorem 1: Denote $\vec{\mathrm{Y}}_t = (y_t, ... y_1, \vec{x}_t', ... \vec{x}_1')$ as the observations of a time series $\{Y_t\}$ and the relevant explanatory variables obtained until time t, the *conditional log likelihood* for model (6.5)-(6.9) is given as:

$$L(\vec{\theta}) = \sum_{t=k+1}^{T} \log f(y_t \mid \vec{x}_t, \vec{\mathrm{Y}}_{t-1}; \vec{\theta})$$

$$= -(T-k)\log(2\pi) - (1/2)\sum_{t=k+1}^{T}\log(\sigma_t^2) - (1/2)\sum_{t=k+1}^{T}\frac{(y_t - f(y_{t-1}, ... y_{t-p}, \vec{x}_t) - \sum_{i=1}^{q}\phi_i e_{t-i})^2}{2\sigma_t^2} \tag{6.10}$$

In (6.10), $\vec{\theta} = (\lambda, \varsigma, \phi, \alpha, \beta)$, and $f(y_{t-1}, ... y_{t-p}, \vec{x}_t)$ is defined as Equation(6.5). Due to the page limit, the proof of Theorem 1 is not given and can be found in [116]. According to Theorem 1, the maximum likelihood estimates of $\lambda, \varsigma, \phi, \alpha, \beta$ should be the estimates that maximize the likelihood function (6.10). An optimization technique, such as Gradient Ascent method [116] should be employed to solve the problem and obtain the parameter estimates.

After $\lambda, \varsigma, \phi, \alpha, \beta$ are estimated, the forecasted mean and variance of the spot price at time t can be given as:

$$Y_t^* = \sum_{i=1}^{p}\hat{\lambda}_i Y_{t-i} + \sum_{j=1}^{l}\hat{\varsigma}_j X_{t,j} + \sum_{k=1}^{q}\hat{\phi}_k \varepsilon_{t-k} + \varepsilon_t \tag{6.11}$$

$$\sigma_t^{2*} = \hat{\alpha}_0 + \sum_{i=1}^{S} \hat{\alpha}_s \varepsilon_{t-S}^2 + \sum_{j=1}^{l} \hat{\beta}_j X_{t,j} \tag{6.12}$$

where $\hat{\lambda}, \hat{\varsigma}, \hat{\phi}, \hat{\alpha}, \hat{\beta}$ are the estimated values of $\lambda, \varsigma, \phi, \alpha, \beta$. The mean and variance of the return of the spot market can be further derived based on (6.11) and (6.12), which is discussed in the following sections. Please note that the above forecasting model is inappropriate for handling spikes since spikes are considered as noise in statistics and usually not modelled.

6.3.2 Long Term Portfolio Selection

As discussed in the introduction, constructing portfolios for a generator involves the consideration of different planning horizons. Different planning horizons will lead to significantly different approaches, which will be demonstrated as follows. The *Long Term Portfolio Selection* (LTPS), whose planning horizon is usually several months, is firstly discussed in this section. Long term portfolio selection mainly considers the problem of allocating generation capacities between forward contracts and the spot market. Moreover, other financial instruments, such as futures and option contracts, can also be considered in LTPS. In this chapter, the main focus is on the forward contract, since in practice it is the widely used way to hedge the long term price risk. Futures contracts, whose positions are not closed out before the maturity date, can be analysed similarly.

As discussed in Section 2, the return distributions of the forward contract and spot market should be firstly derived before the portfolio selection model can be applied. Assume that the cost function of a generator follows a quadratic function of its dispatched generation capacity:

$$C(g) = a + b \cdot g + c \cdot g^2 \tag{6.13}$$

where g denotes the dispatched capacity in the trading interval. The parameters a, b, c are the private information of the generator.

According to [112, 113], the *return* of an investment is defined as the revenue minus the cost, divided by the cost. Note an important fact that, all the power of a generator is actually dispatched through the spot market. For the power that sold through the forward contract, the generator just receives or pays the difference between the forward strike price and spot price when transactions are settled. Therefore, when calculating the costs, the power sold through the forward contract and spot market should be considered together, rather than separately.

In practice, the generator usually selects fulfilling the obligation of forward contracts as their priority. Therefore, denote g_f and g_s as the power sold through the forward contract and spot market respectively, the cost of selling power through forward contracts can be expressed as:

$$C(g_f) = a + b \cdot g_f + c \cdot g_f^{\,2} \tag{6.14}$$

The cost of selling power through the spot market is:

$$\begin{aligned} C(g_s) &= C(g_f + g_s) - C(g_f) \\ &= a + b \cdot (g_f + g_s) + c \cdot (g_f + g_s)^2 - a - b \cdot g_f - c \cdot g_f^{\,2} \\ &= b \cdot g_s + 2c \cdot g_f \cdot g_s + c \cdot g_s^{\,2} \end{aligned} \tag{6.15}$$

Based on Eqs. (6.14) and (6.15), let p_f, p_s denote the forward strike price and spot price, the return of the forward contract can be calculated as:

$$r_f = \frac{p_f \cdot g_f - C(g_f)}{C(g_f)} \tag{6.16}$$

The forward strike price p_f is usually determined by the generator and its customer together. The negotiation of the forward strike price is beyond the scope of this chapter. It is assumed that it has been determined and is a fixed value.

It is also assumed that the spot market is perfectly competitive, which means that a generator can bid at a very low price to ensure it is dispatched without significantly decreasing the spot market price. The return of the spot market can then be calculated as:

$$r_s = \frac{p_s \cdot g_s - C(g_s)}{C(g_s)} \tag{6.17}$$

where p_s denotes the spot electricity price.

After deriving the mathematical formulations of r_f, r_s, we now discuss how to calculate their means and variances. In our problem setting, p_f is assumed to be a fixed value. g_f is the quantity to be optimized, thus is also fixed in each iteration of the optimization process. Therefore, r_f is fixed in each optimization iteration. We then have:

$$\mu(r_s) = \frac{p_f \cdot g_f - C(g_f)}{C(g_f)} \tag{6.18}$$

$$\sigma^2(r_f) = 0 \tag{6.19}$$

For r_s, since the only random variable in r_s is p_s, the mean and variance of r_s can be given as:

$$\mu(r_s) = \frac{g_s}{C(g_s)} \cdot \mu(p_s) - 1 \tag{6.20}$$

$$\sigma^2(r_s) = \left[\frac{g_s}{C(g_s)}\right]^2 \cdot \sigma^2(p_s) \tag{6.21}$$

Till now, the only remaining problem is to estimate the mean and variance of the spot price. Forecasting the spot price several months ahead is a long term forecasting problem. It is difficult to obtain accurate forecasts and not many advanced forecasting techniques are currently available for this problem. In this chapter, a simple price model is employed. Denote the planning period as period t. For the mean spot price $p_s(t)$ at period t, we assume that it is a function of the mean spot price at period t-1, as well as GDP and system demand at period t. We thus have:

$$p_s(t) = \rho \cdot p_s(t-1) + \psi \cdot GDP(t) + \omega \cdot Demand(t) \tag{6.22}$$

Estimating ρ, ψ, ω is equivalent to perform a linear regression on the historical data of the spot price, GDP and system demand [117].

The variance of p_s can be obtained by simply calculating the variance of p_s in the corresponding period in last year. For example, if a generator is designing the portfolio for Jul 2007, it can then use the variance of the spot price in Jul 2006 as the estimate. Substituting the estimates of mean and variance of p_s into Equations (6.20) and (6.21), the $\mu(r_s)$ and $\sigma^2(r_s)$ can be obtained.

The means and variances of the forward contract and spot market derived in this section can be substituted into the portfolio selection model (6.4) to obtain the optimal portfolio. The means and variances of other markets and instruments can be derived in similar ways. If only the forward contract and spot market are considered, the covariance between them is zero, since r_f is not a random variable. If other markets or contracts are involved in the problem as well, the covariance matrix then has to be estimated, which will be investigated in our further research.

6.3.3 Short Term Portfolio Selection

Short Term Portfolio Selection (STPS) designs the portfolio several days in advance. The generator usually sells a large amount of its power by submitting bids to the day ahead spot market. Therefore, designing bidding strategies is an important task in STPS. Moreover, the spot electricity price can seriously fluctuate within days. The short term price risks can be hedged with a number of financial instruments, such as futures or options. The mathematical model for short term portfolio selection has been derived as well. This result will be discussed in a future publication.

6.4 Differential Evolution (DE)

The proposed approach of selecting optimal portfolio is an optimization problem. A DE based optimizer is selected to solve this optimization problem. Although DE had been discussed in detail in Chapter 3, for the sake of completeness, the DE used in this portfolio optimisation model is briefly reviewed here. DE [118] is a stochastic direct search and optimization method. It is widely accepted as an accurate, fast and robust optimization method. The main advantage of DE is its simplicity and therefore ease to use in solving optimization problems requiring the minimization process with real valued and multi-modal (multiple local optima) objective functions. A non-uniform crossover, which makes use of child vector parameters to guide through the minimization process, is employed in DE. As shown in Figure 6-1, the mutation operation with DE is performed by arithmetical combinations of individuals rather than perturbing the genes in individuals with small probability as compared with one of the most popular Evolutionary Algorithm (EA), GA. Another main characteristic of DE is that, it can search directly with the floating point representation, rather than the binary representation as used in many basic EAs. The characteristics together with other factors of DE make it one of the most suitable optimisation tools for the optimal portfolio selection problem.

It should be noted that the optimization problem in (6.4) can be modified into a *Mixed*

Integer Programming (MIP) model which can be solved more efficiently by commercial software such as CPLEX [119]. However, for the problem in this chapter, a number of assumptions and simplifications have to be made in order to build the MIP model. It can then be solved by commercial software such as CPLEX. In this chapter, we would like to explore the optimal portfolio with the original objectives and constraints in order to make the analysis as comprehensive as possible. DE, like other EAs has been proven to be able to locate the global optimal solution and more importantly can handle nonlinear, non-convex and discontinues optimization problems. Research has proven that compared with other EAs, DE is very efficient for global optimization problem. Therefore, DE is used in this chapter. Moreover, with the model presented in the chapter, it can be easily modified into MIP form if needed by a user.

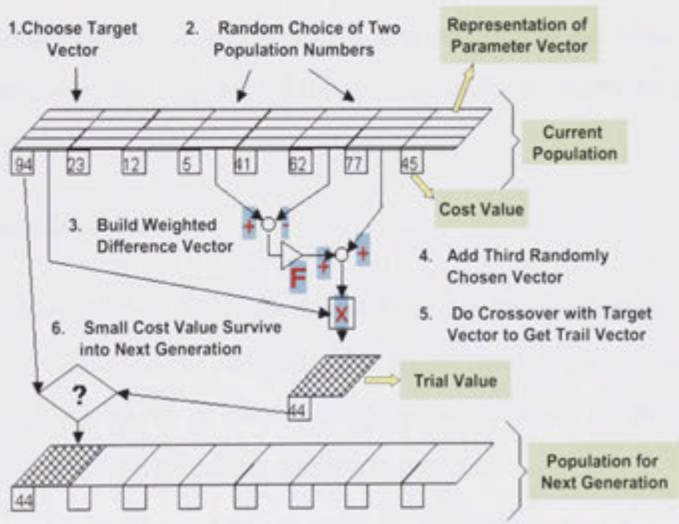

Figure 6-1 A Typical Differential Evolution (DE) [76]

6.5 Case study

6.5.1 Experiment Setting

In this section, the effectiveness of the proposed approach is demonstrated with data in a real market. The Australian NEM is selected for case studies in this chapter. The price model of the spot market is built based on the market data from 2006 to 2007, which is published in the website of NEM [42].We assume that there is a GENCO who has two 197-MW fossil generators located in the Queensland market of Australia NEM [42]. The information of the experiment is given in Table 6-1.

Table 6-1 Experiment Setting Information

Private Information		Public Information	

Cost Function Parameters	a = 108;
	b = 5.7;
	c = 0.02;
		Historical Data of the Spot Market	Queensland Market, from 2006 to 2007

Risk Aversion Degree	1-10	Forward Contract Price ($/MWh)	55

The case study has two main objectives:

- By comparing the performance of the proposed portfolio with other portfolios, it will be proved that the proposed approach is able to achieve a proper trade off between return and risk.
- By altering the risk aversion degree and the parameters of the cost function of the generator, the impacts of these parameters on portfolio selection will be investigated.

6.5.2 Experiment Results

It is assumed that in 30 Jun 2007, the GENCO is designing its portfolio for Jul 2007. Model (6.22) is employed to estimate the mean spot price in Jul, and then the optimization problem (6.4) is solved with corresponding optimisation tool. The portfolio obtained with the proposed method is given as:

Table 6-2 The Portfolio for July 2007 (A=5)

Asset	Proportion	Capacity (MW)
Forward Contract	33%	130.02
Spot Market	67%	263.98

The corresponding return parameters can then be calculated as:

Table 6-3 Return Parameters (A=5)

Asset	Mean of Return (%)	SD of Return (%)
Forward Contract	2.71	0
Spot Market	4.96	2.01
Proposed Portfolio	3.45	1.35

To validate that the proposed portfolio is superior to alternative strategies, its actual revenue is calculated with the real market data of Jul 2007, then compare it with the performances of the other two strategies, which are allocating all of the capacity to the spot market and allocating all of the capacity to the forward contract.

Table 6-4 Performance Comparison of Different Portfolios (a=5)

Portfolio	Expected Revenue (M$)	Actual Revenue (M$)	Revenue SD ($)
Allocating all capacity in spot market	3.4893	3.3887	10651
Allocating all capacity in forward contract	3.1205	3.1205	0
Proposed Portfolio	3.3676	3.3672	4135.9

In Table 6-4, the actual revenue is calculated by assuming that the corresponding portfolio is applied, while spot market prices are set as the real market prices in Jul 07. As shown in Table 6-4, if the proposed portfolio is employed in Jul 07, its revenue will be close to the actual revenue obtained by allocating all of the capacity to the spot market. However, the standard deviation of its revenue is much smaller, indicating that it has much lower risks than selling all of the power into the spot market. Moreover, the difference between the actual revenue and expected revenue of the proposed portfolio is insignificant. This implies that the proposed method can appropriately estimate the return characteristics of different assets.

The risk aversion degree represents the generator's attitude towards risk, which has significant impact on the portfolio selection. The relationship between the risk aversion degree and optimal proportions of assets is plotted in Fig. 6-2. As observed, the forward contract will have a higher proportion in the proposed portfolio if the risk aversion degree rises. This phenomenon is reasonable since allocating greater capacity to the forward contract can decrease risks.

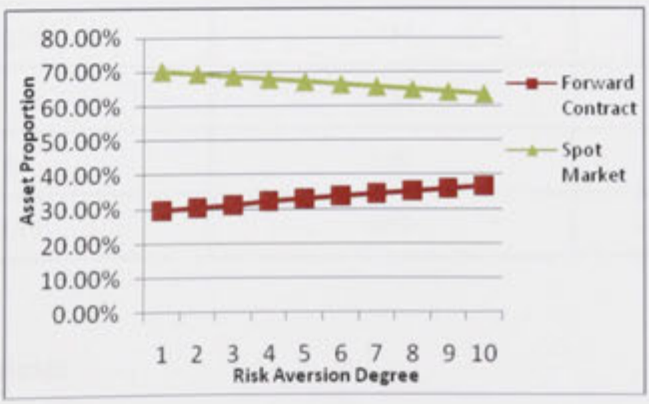

Figure 6-2 Risk Aversion Degree v.s. Asset Proportions

The risk aversion degree and the corresponding means and standard deviations of the proposed portfolio are given in Fig. 6-3. Unsurprisingly, the standard deviation of the return decreases as risk aversion degree increases, which indicates that the generator tends to select a less riskier portfolio if it is more risk averse.

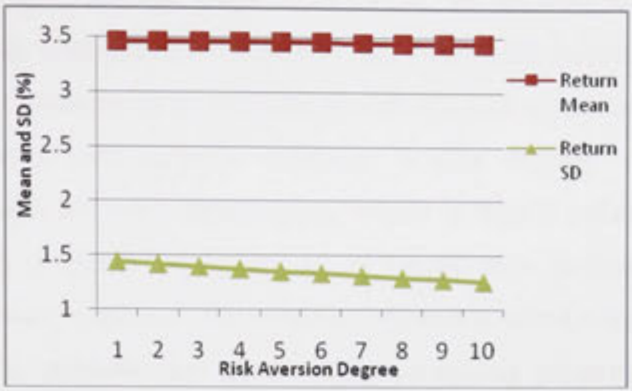

Figure 6-3 Risk Aversion Degree v.s. Return Mean and SD

The costs of the generator are other factors that can significantly influence its portfolio selection. To study the impact of generator's costs, the parameters a, b, c are multiplied by a scale coefficient s. The corresponding optimal portfolio is then obtained and illustrated in Table 6-5. As shown in Table 6-5, the return mean and SD both decrease as the scale coefficient s increases. A greater s indicates greater generation costs. It is more difficult for the generator to gain profits in the spot market if its costs rise. Therefore, higher costs weaken the generator's incentive to take risks. It thus tends to select forward contracts to hedge its risks.

Table 6-5 Cost Scale Coefficient and Corresponding Optimal Portfolio

S	Return Mean of the Proposed Portfolio(%)	Return SD of the Proposed Portfolio(%)	Portion of the Forward Contract
0.6	6.37	1.9	0.346
0.8	4.54	1.51	0.354
1	3.44	1.25	0.366
1.2	2.7	1.07	0.383
1.4	2.17	0.93	0.410

6.6 Conclusions

In deregulated electricity markets, generators have a difficult task of selecting the optimal portfolio, which consists of a variety of markets and contracts. Theoretically, the portfolio selection problem aims at allocating generation capacities to proper markets and financial contracts, so as to achieve the optimal trade-off between return and risk. In this chapter, a method is proposed to solve the generator portfolio selection problem. According to different planning horizons, the problem is divided into two sub-problems, long term portfolio selection and short term portfolio selection. The authors derive the mathematical formulations of different asset returns for both the long term and short term portfolio selection. A time varying volatility model is introduced to model the spot market price, which is highly volatile. The portfolio selection problem is finally formulated as an optimization problem, which can be solved by a DE based optimizer. The proposed method is tested with real market data. Its effectiveness is demonstrated by obtaining promising performance in the case studies.

With the new methodologies of this chapter, an overall package of a risk management tool for GENCOs is built. This package provides optimal bidding strategies for the generator companies with market uncertainties and incomplete information. It also provides a portfolio optimisation solution methodology.

In the following chapter, another important functionality – price modelling – for the proposed framework will be presented.

Chapter 7

Electricity Market Clearing Price Forecasting

In a competitive electricity market, price modelling is one of the key activities for both ISO and market participants. GENCOs need such information in forming their market strategy in view of bidding and hedging contacts. Transmission companies need such information in formulating market benefits to justify transmission network planning options. In this chapter, fuzzy IA and RBF neural network based models are proposed for MCP forecasting with detailed real market data analysis.

7.1 Introduction

In the competitive electricity market, price forecasting can help to build up effective cost risk management plans for the participating companies. Currently, market participants use different instruments to control and minimize the risks as a result of the market reference price. If the market reference price can be properly predicted, generators and retailers can reduce their risks and maximize their outcomes further. Because of the great similarity between price and load forecast [120], there are many approaches we can borrow from load forecasting. In previous studies, regression models [121], neural networks [122-125], and data mining [126, 127] based techniques have been employed for this purpose. Also the statistic time series models including ARIMA [128] and GARCH models [93] have been proved to be effective with satisfactory prediction performance. However, according to references [129], neural networks methods for forecasting have been shown to be able to give better performance in short-term electricity price forecasting.

Due to a number of advantages compared with other types of neural networks, such as better approximation capabilities, simpler network structures and faster learning algorithms, *Radial Basis Function* (RBF) neural networks are continuously increasing their popularity in nonlinear system modelling [123]. RBF neural networks can approximate any continuous function defined on a compact set to any prescribed degree of accuracy by sufficiently expanding the size of network [130, 131]. RBF neural networks form a special network architecture, which consists of three layers, namely the input, hidden and output layers. The structure of a typical Multi-Input Single-Output (MISO) RBF neural network is shown in Figure 7-1.

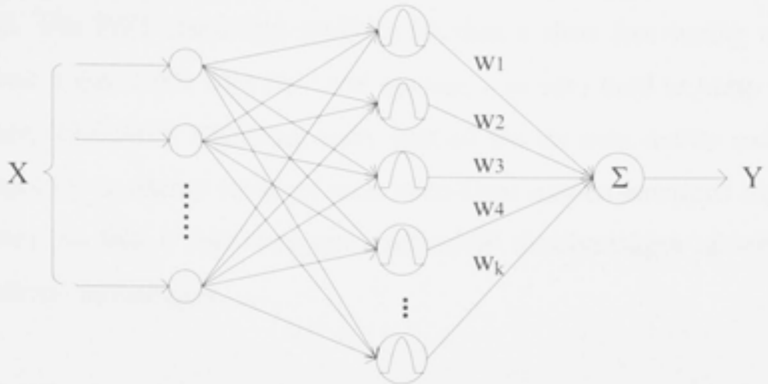

Figure 7-1 Structure of a Typical MISO RBFNN

However, how to choose suitable network structures has always been a problem which blocks the wide application of RBF neural networks. A small network may never converge, while a large one converges fast but lacks generalization ability. Meanwhile, due to the great influence of cluster centres and radii of the RBF on the overall performance of RBF neural networks, an effective approach should be introduced. Currently, the majority of the training schemes for RBF neural networks can be classified as one-phase learning and two-stage training.

- One-phase learning. With this learning procedure, the parameters of hidden layer activated functions and the output connection weights are adjusted simultaneously with objective, which is minimization of network output errors.
- Two-stage training. Two layers of RBF neural network are trained separately; first the parameters of hidden layer activated functions are determined in self-organizing manner or assigned randomly in advance, followed by output connection weights adjusted through kinds of supervised approaches.

7.2 Fuzzy Immune Algorithm (FIA)

The global optimization approaches are mainly the EAs, such as GA, PSO, and DE. They can be used to train the neural networks due to their global optimization capabilities. Although the heuristic methods do not always guarantee discovering globally optimal solutions in finite time, they often provide fast and reasonable solutions. Although GA can ensure that the colony evolves and the solutions change continually, it may lack strong capacity of producing the best offspring individuals and causes the speed to slow when near global optimum and sometimes trapped into local optima. DE is a very powerful evolutionary algorithm, but the greedy updating method and intrinsic differential property usually leads the computing process to be trapped by local optima. The PSO converges quickly, but has a slow fine-tuning ability of the solution. Once it gets stuck into the local optima, it is very hard to jump out from the local optimum. Generally speaking, each method has its own merits and drawbacks. Many attempts try to merge some of their individual implementations together into a new algorithm, so that it can overcome individual disadvantages as well as benefit from each others' advantages.

With the development of immunology and research methods, the mechanism of biological immune system has gradually been discovered by researchers. Because of the powerful ability of information processing and special characteristics such as diversity, adaptive trait, biologic immune system has become a hot spot of artificial intelligence. *Immune Algorithm* (IA) imitates the principle of the defence system annihilates foreign disease-causing bacteria or viruses through self-learning and self-adjusting. Although IA is very similar to GA, there are essential differences in the production theory for memory and population. Compared with GA and other EAs, IA promotes general search ability through the mechanism based on memory pool. At the same time, it realizes the function of self-adjusting by calculating affinity and concentration. To some extent, it avoids premature convergence. Here a new IA is proposed, which uses the fuzzy system to realize the adaptive selection of two key parameters (crossover possibility and mutation possibility), addressing the convergence speed and calculation precision problems in the basic IA. The steps of the FIA are depicted as shown in Fig. 7-2 [132].

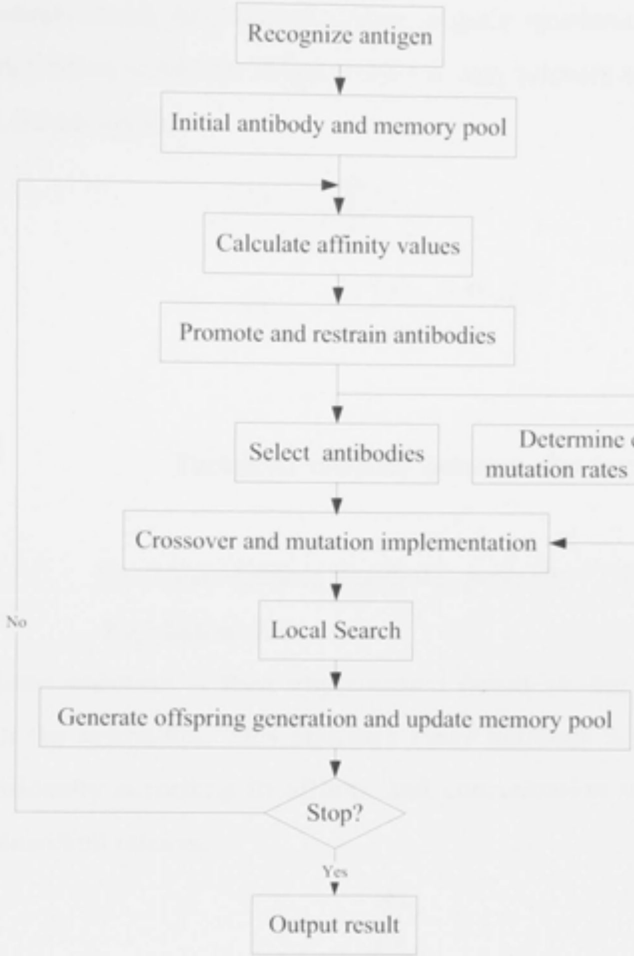

Figure 7-2 Flowcharts of a Fuzzy Immune Algorithm

The calculation strategy of FIA, [132], is represented as follows:

Step-1. For the practical problems, the antigens and antibodies in the immune system represent the objective functions and feasible solutions, respectively. IA uses affinity and concentration values as discriminators of the quality of solutions represented by the antibodies in one population which are calculated by:

$$As_{i,t} = r \times (1-r)^{i-1} \tag{7.1}$$

where,

- r is the random number in the interval in (0,1);
- i is the location index of antibodies in current population which are arranged in terms of function values in ascending sequence; and
- $As_{i,t}$ is the affinity value of antibody i of generation t.

Then the individuals should be returned to their original locations. The most attractive feature of this definition is that the affinity value is only relevant to the locations index rather than real fitness values.

$$Cs_{i,t} = \frac{1}{p}\sum_{i=1}^{p} Ks_{Ab_{mn}} \tag{7.2}$$

$$Ks_{Ab_{mn}} = \begin{cases} 1, & \|Ab_{m,t} - Ab_{n,t}\| < l \\ 0, & otherwise \end{cases} \tag{7.3}$$

where,

$\|\cdot\|$ Euclidean distance between the two randomly selected antibodies;

l Euclidean distance threshold, generally l = 1e-6;

p Population size.

Step-2. A roulette selection is then implemented based on the computed selection probabilities for the antibodies. This allocates every antibody a probability of being selected proportionally according to affinity and concentration values. The equation for computing selection rates is:

$$Ps_{i,t} = \frac{\dfrac{As_{i,t}}{Cs_{i,t}}}{\sum_{i=1}^{p}\left\{\dfrac{As_{i,t}}{Cs_{i,t}}\right\}} \tag{7.4}$$

Step-3. Crossover and mutation are implemented at this step. Crossover is one of the primary IA operators that promote the new region exploration ability in the search space. Generally, crossover rate should be chosen relatively large [133], between 0.7 and 1.0. Mutation is another IA operator which guarantees the diversity of the population. In the reference [133], the mutation rate should be chosen between thousandths and hundredths. According to reference [134], the crossover and mutation rates can be adjusted by statistical methods, SVM or neural networks. However, when the above methods were compared with the fuzzy system approach proposed here, we found that the fuzzy system approach makes better contributions to the IA in both time consumption and calculating precision.

Crossover and mutation fuzzier input data are $f_d(t)$, Pc and $F_d(t)$, Pm in which $f_d(t) = \dfrac{\overline{f}(t) - f_{\min}(t)}{f_{\max}(t) - f_{\min}(t)}$ and $\overline{f}(t), f_{\min}(t), f_{\max}(t)$ are the average, minimum and maximum function values of t iterations respectively. ΔPc and ΔPm are the changes in crossover and mutation rates between t and $t-1$ iterations which also are fuzzier output data. The membership functions for input $f_d(t)$, Pc and output ΔPc of crossover fuzzier are shown in Figs. 7-3 – 7-5. The membership functions for $f_d(t)$, Pm, ΔPm of mutation fuzzier can be drawn in the same way, shown in Figs. 7-6 – 7-7. According to a great deal of experimental data and expert knowledge, the fuzzy decision for ΔPc is made and shown in following Tables 7-1 and 7-2. Using the same theory, we can produce the fuzzy decision table for ΔPm.

In these figures and tables, the following notations are used:

Negative Huge (NH), Negative Large (NL), Negative Medium (Nm), Negative Small (NS), Zero (ZE), Positive Small (PS), Positive Medium (PM), Positive Large (PL), and Positive Huge (PH).

Figure 7-3 The chart of membership functions for input variable

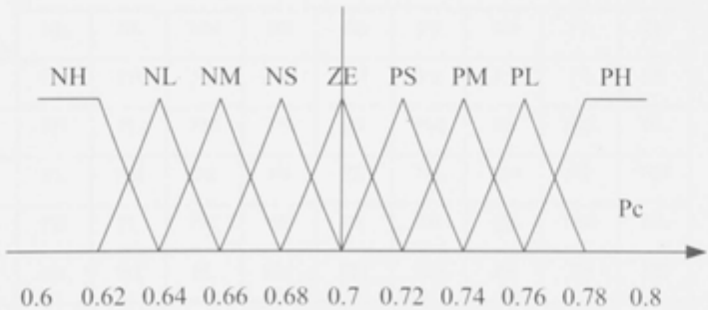

Figure 7-4 The chart of membership functions for input variable

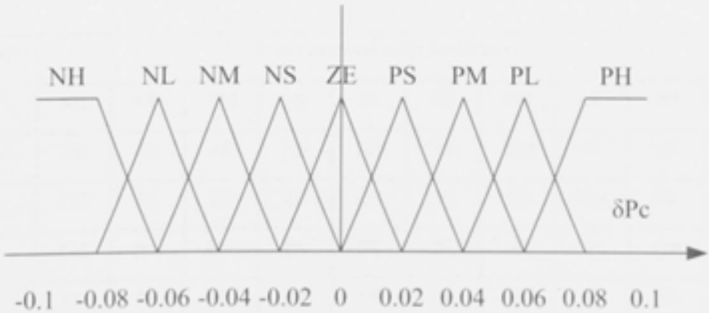

Figure 7-5 The chart of membership functions for output variable

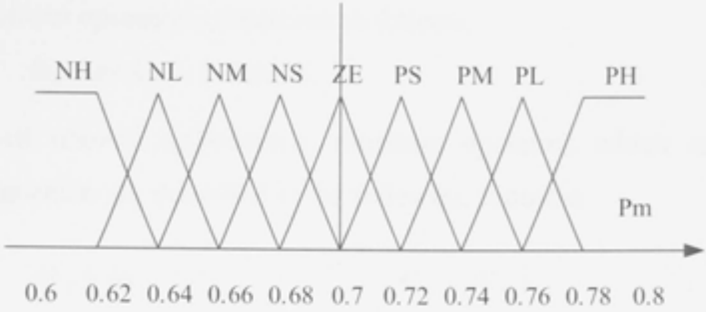

Figure 7-6 The chart of membership functions for input variable

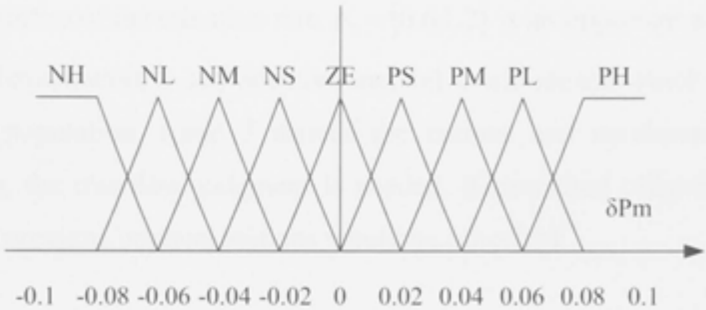

Figure 7-7 The chart of membership functions for output variable

Table 7-1 The chart of membership functions for output variable

$\Delta Pc(t)$ / $f_d(t)$	Fuzzy decision table for $\Delta Pc(t)$								
	NH	NL	NM	NS	ZE	PS	PM	PL	PH
ZE	PH	PH	PL	PM	PM	PS	PS	PS	ZE
PS	PH	PL	PM	PS	PS	PM	NS	NM	NL
PM	PL	PM	PS	PS	ZE	NS	NM	NL	NH
PL	PH	PL	PM	PS	PS	ZE	NS	NM	NL
PH	PH	PH	PL	PM	PM	PM	PS	PS	ZE

Table 7-2 The chart of membership functions for output variable

$\Delta Pm(t)$ / $f_d(t)$	Fuzzy decision table for $\Delta Pm(t)$								
	NH	NL	NM	NS	ZE	PS	PM	PL	PH
ZE	ZE	ZE	ZE	NS	NS	NM	NM	NL	NH
PS	PM	PS	PS	ZE	ZE	NS	NS	NM	NL
PM	PM	PM	PM	PS	PS	ZE	NS	NS	NM
PL	PL	PL	PM	PS	PS	ZE	NS	NS	NS
PH	PH	PH	PL	PM	PM	PM	PS	PS	ZE

An arithmetic crossover operator is described as follows:

$$Ab_{i,t}^{'} = b \times Ab_{m,t} + (1-b) \times Ab_{n,t} \tag{7.5}$$

And two improved uneven self-adaptive mutation operators which are selected randomly in the algorithm are described as the following formulas:

$$Ab_{i,t}^{'} = Ab_{i,t} + (-1)^{t} \times \left(1 - b^{\left(1-\frac{t}{T}\right)^{r}} \right) \times \left(Ab_{m,t} - Ab_{n,t} \right) \tag{7.6}$$

$$Ab_{i,t}^{'} = Ab_{i,t} + F_0 \times 2^{e^{1-\frac{T}{T-t+1}}} \times \left(Ab_{m,t} - Ab_{n,t} \right) \tag{7.7}$$

Due to the uncertainties of the mutation rate, $F_0 = [0.6, 1.2]$ is an important parameter in the mutation implementation, a self-adaptive method is introduced which guarantees the diversity of population. t and T denote the current and maximum iteration, respectively. Also, the overflow judgment is needed, if generated offspring exceeds given bounds, the previous implementations would be cancelled.

Step-4. Finally, antibodies which have high affinity values will evolve into next iteration and be added into the memory pool. A given number of new antibodies which comply with Gauss distribution around the best antibody will be added into population, to replace those which have lower affinity values. Meanwhile, due to the fact that the massively parallel search is resource intensive, only small populations can be evolved in short time. Thus, the inadequate sampling of the search space leads to the loss of diversity information and thus to fast premature convergence. To overcome this drawback, a diversification mechanism for introducing is required. This can be achieved to some degree by neighbourhood search, Memetic Algorithm (MA) [135]. Then the algorithm returns to step-2, unless the maximum number of iterations is reached. Otherwise the algorithm stops as the network corresponding to the smallest prediction error is selected.

7.3 Configuration of The RBF Neural Network

7.4.1 Learning Theory

For typical RBFNN, if w_i is output weights, $\phi_i(X, C_i)$ is the output of i^{th} neuron, $X=[x_1, x_2, \ldots, x_m]$ is input vector, C_i is the hidden node centre locations of i^{th} neuron, y is linear summation of output of hidden layer neurons. If the RBF is Gauss function

$$\phi_i(X,C_i) = e^{-\frac{\sum_{j=1}^{m}(x_j - c_i^j)^2}{(c_i^{m+1})^2}} \tag{7.8}$$

$$y = \sum_{i=1}^{n} w_i \phi_i(X,C_i) + e_n \tag{7.9}$$

For one set of training data, the equation can be transformed into

$$Y = \sum_{i=1}^{n} w_i Q_i + E_n \tag{7.10}$$

And then

$$Y = w_1 Q_1 + E_1 \tag{7.11}$$

$$E_1 = w_2 Q_2 + E_2 \tag{7.12}$$

$$E_{n-1} = w_n Q_n + E_n \tag{7.13}$$

Therefore the given equations can be transformed into

$$E_{n-1} = w_n R_n + w_n (Q_n - R_n) + E_n \tag{7.14}$$

Obviously the influence of Q_n–R_n can be eliminated by change $w_1, w_2, ..., w_{n-1}$ into $w_1^{'}, w_2^{'}, ..., w_{n-1}^{'}$ and then

$$E_{n-1} = W_n^{'} R_n + E_n \tag{7.15}$$

$$\begin{aligned} \|E_n\|^2 &= \left(E_{n-1} - W_n^{'} R_n\right)^T \left(E_{n-1} - W_n^{'} R_n\right) \\ &= E_{n-1}^T E_{n-1} - 2W_n^{'} E_{n-1}^T R_n + W_n^{'2} R_n^T R_n \\ &= \|E_{n-1}\|^2 - 2W_n^{'} E_{n-1}^T R_n + W_n^{'2} R_n^T R \end{aligned} \tag{7.16}$$

From above equation, we can conclude that the target of the n^{th} training is to find W'_n and C^n in order to minimize $\|E_n\|^2$.

7.4.2 Training Steps

Because a set of orthogonal sequential vectors R_1, R_2, …, R_n is needed, which can be calculated by Q_1, Q_2, …, Q_n

$$R_1 = Q_1 \tag{7.17}$$

$$\alpha_{in} = R_i^T Q_n / R_i^T R_i \tag{7.18}$$

$$R_n = Q_n - \sum_{i=1}^{n-1} \alpha_{in} R_i \; (n = 2,3...) \tag{7.19}$$

From the discussion above, we can get to know that

$$\frac{\partial \|E_n\|^2}{\partial w_n^{'}} = -2E_{n-1}^T R_n + 2w_n^{'} R_n^T R_n \tag{7.20}$$

$$w_n^{'} = E_{n-1}^T R_n / \left(R_n^T R_n\right) \tag{7.21}$$

Here the R_n can be optimized by the fuzzy IA. After that the output connection weights can be calculated by

$$W = \left(Q^T Q\right)^{-1} Q^T Y \tag{7.22}$$

7.4 Forecasting Simulation Examples

7.4.1 Benchmark Function Simulation

In order to mathematically illustrate the effectiveness of the proposed approach, a bench mark chaos time series is used as the second case study. The orientation of time series prediction involves mainly the setup of prediction horizons and the type of chaotic time series (e.g. noise-free or noised data). According to the prediction horizons, the prediction falls simply into two categories: short-term prediction and long-term prediction. Both noise-free and noised Mackey-Glass chaos time series [136] are used here. The time series can be generated by the following difference equation:

$$x(t+1) = a\frac{x(t-\tau)}{1+x(t-\tau)^c} + (1-b)x(t) \tag{7.23}$$

The chaos time series generated by the above equation, will illustrate chaos characteristics when $\tau \geq 17$. So this equation is usually applied to test the learning and generation ability of neural networks. In this chapter, the parameters are set as follows:

$$a = 0.2, b = 0.1, c = 10, \tau = 17 \tag{7.24}$$

Mackey-Glass chaos time series long-term prediction is more difficult than short-term prediction. It requires more neurons and longer training time. However, too many neurons in the hidden layer may result into decreasing generation ability with the network. The proposed method can be used to reduce the number of neurons of neural networks and in the same time to improve the generation ability. The following function is chosen to approximate the Mackey-Glass chaos time series:

$$\begin{cases} x(t+n) = f\left[x(t), \cdots, x(t-2), x(t-3)\right], n = 5,10 \\ x(t) = 1.2, t = 1,2, \cdots 17 \end{cases} \tag{7.25}$$

Total of 300 data points were generated with the first 200 data for training the neural network and the remaining data to check the generalization ability of the network. The results are provided in Figs. 7-8 – 7-11.

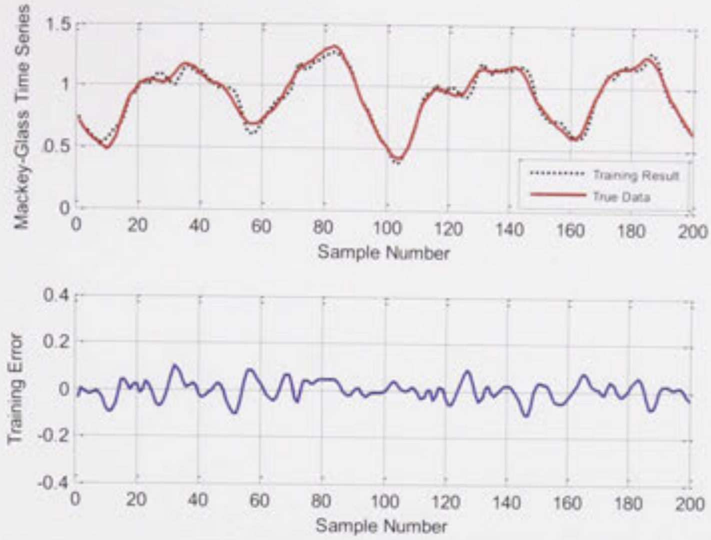

Figure 7-8 FIA RBF Chaos Time Series Prediction Training Result ($\Delta T=5$)

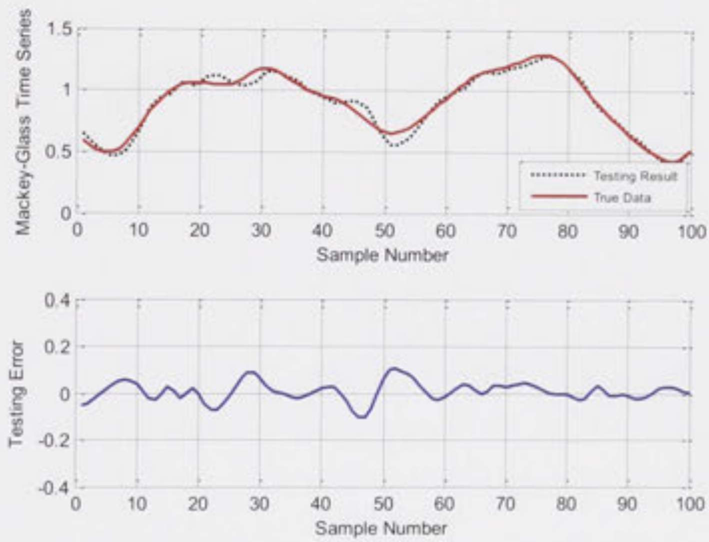

Figure 7-9 FIA RBF Chaos Time Series Prediction Testing Result ($\Delta T=5$)

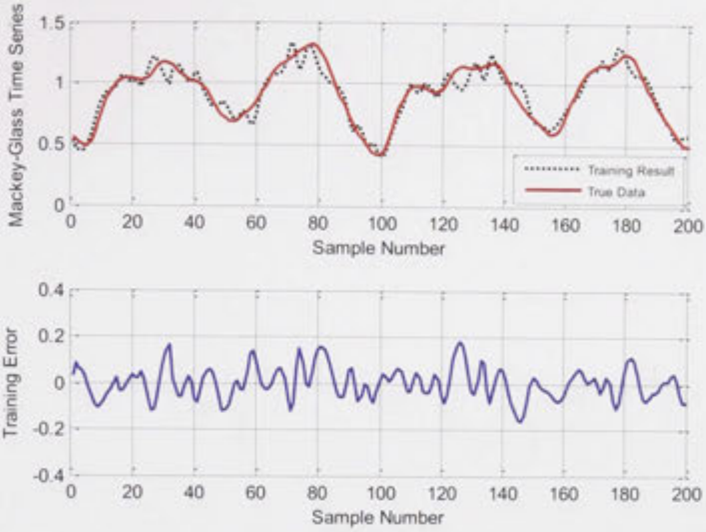

Figure 7-10 FIA RBF Chaos Time Series Prediction Training Result ($\Delta T=10$)

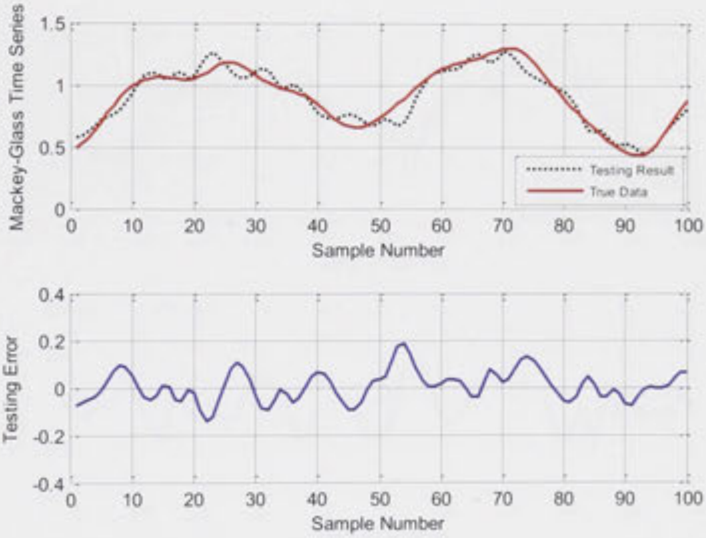

Figure 7-11 FIA RBF Chaos Time Series Prediction Training Result ($\Delta T=10$)

In order to test the robustness of the proposed algorithm, the normal distribution noise was added into the training data. The result shows that if the noised data were used for network training, the prediction performance will be slightly influenced. The best results are shown as Fig.7-12 and Fig.7-13. Summary of the studies are given in Table 7-3.

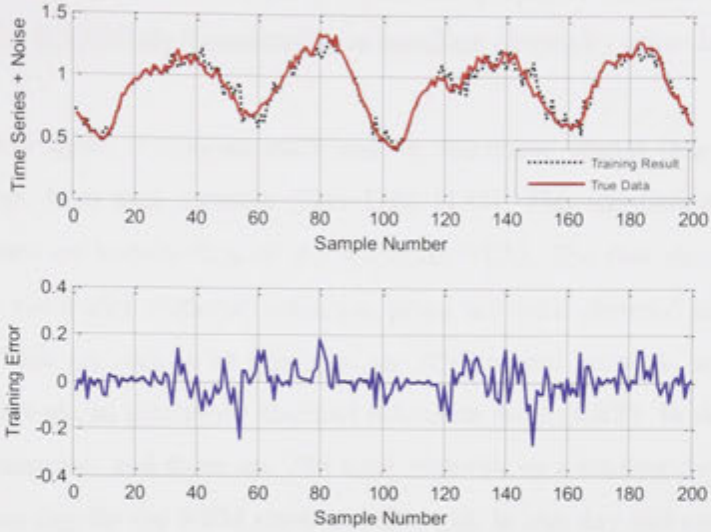

Figure 7-12 FIA RBF Chaos Time Series Prediction Training Result ($\Delta T = 5$, Add noise)

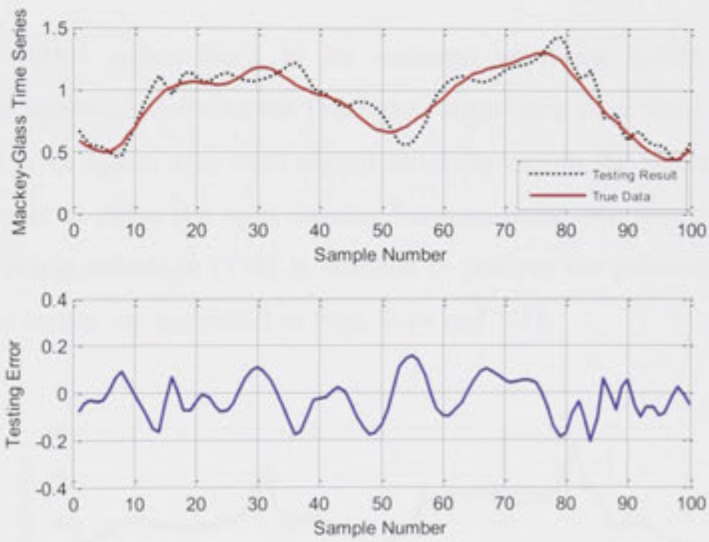

Figure 7-13 FIA RBF Chaos Time Series Prediction Testing Result ($\Delta T = 5$)

Table 7-3 Summary of Chaos Time Series Prediction Experiment Data

Mackey-Glass Time Series	$\Delta T = 5$	$\Delta T = 10$	$\Delta T = 5$ +Noise
Neuron Number	11	24	17
Training MSE	1.633e-3	4.523e-3	6.173e-3
Testing MSE	1.688e-3	4.222e-3	6.777e-3

7.4.2 Electricity Reference Price Forecasting

In this section, the proposed forecasting method is tested with the Queensland electricity regional reference price. The Queensland market is part of the Australian NEM which is composed of the states of New South Wales, Victoria, South Australia, Queensland and Tasmania. The market price data are taken from the NEMMCO website [42]. It is widely accepted that the electricity price is highly volatile and difficult to predict. In the following analysis, the proposed method will be used on such data series to illustrate its capability in handling electricity price data series.

There are three types of seasons each year in Australia: winter (May-Aug), middle (Mar-Apr, Sep, Oct) and summer (Nov-Feb) [137]. The simulation experiment is performed based on history data of the Australia NEM. The two main factors which influence the electricity regional reference price are total demand and dispatchable generation, which are chosen as inputs of the RBF neural network, and the output is the relevant day-ahead electricity regional reference price (RRP). In the NEM, a time interval is 5 minutes, and there are 288 time intervals in a trading day. According to NEM, a trading day for the NEM starts at 4:00 A.M. in one day and ends at 4:00 A.M. the next day [42].

Normally the price spikes need to be removed as noise before the prediction algorithms are applied; otherwise the prediction algorithms may result in large errors. However, the price spikes also have significant influence in the electricity market. In this test, in order to strike the right balance between these two aspects, we adopt the wavelet de-noising technique [138] is adopted to process the collected data samples. The prediction results are presented in Figs. 7-14 and 7-15.

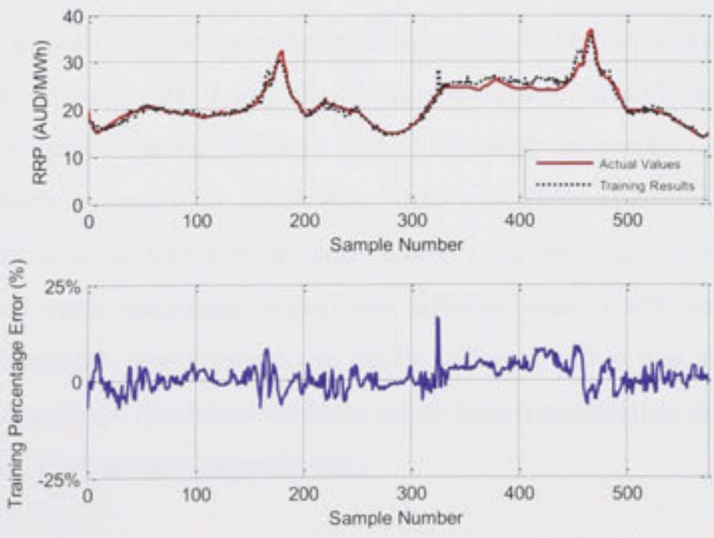

Figure 7-14 Electricity Reference Price Forecasting Training Result

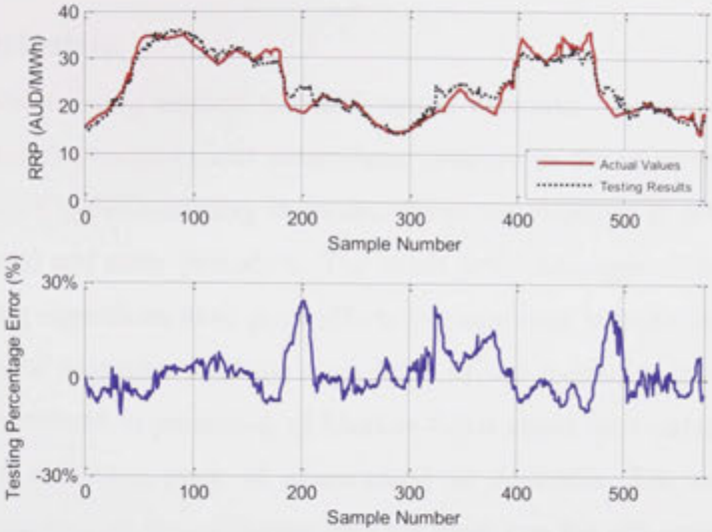

Figure 7-15 Electricity Reference Price Forecasting Testing Result

7.4.3 Results Analysis

As clearly shown in the result, it can be concluded that, the proposed hybrid training method for RBF neural network overcomes the blindness in choosing a suitable network structure. Obviously the neural network optimized by this self-learning method ensures the overall generation ability. The promising network predictions performance on the price data illustrated the efficiency of the proposed method.

It is unpractical to predict a whole year's data with one artificial neural network model because it is a nontrivial task and the processing would be very complicated due to a large amount of data involved, and alternative approaches should be used, although the result might be useful for GENCOs or ISOs. Moreover, the weeks-ahead and months-ahead long horizon prediction lacks strict theory basis, because there is not certain relationship between different weeks and months, only some similarity could be found from the same week and month in previous different years. Furthermore, the dates of week days, weekends, and holidays are totally different within two years. In addition, the factors of weather condition could be taken into consideration and some extreme contingencies [139] are also unpredictable.

The most effective approach for regional reference price prediction is to develop specially designed tools for holiday and the spike effect, and take into account the historical information of previous years, as well as other relevant data such as weather conditions.

7.5 Conclusions

A new hybrid training method for RBF neural networks was proposed in order to optimize network structures and parameters, contrary to the most standard *Artificial Neural Network* (ANN) training methods, where the structure is selected by a time consuming trial and error procedure. The result achieved suggests that, the proposed hybrid training algorithms have good effects on improving stability and generalization ability of neural networks. And the availability of this method is proved by applying RBF neural networks in predicting of Mackey-Glass chaos time series and forecasting of electricity reference price of Queensland in Australia. The successful neural network forecasting on the validation data set illustrates the efficiency of the method and showed that it can be used as a reliable tool for forecasting modelling.

In the following chapter, a risk assessment framework will be presented to further the usefulness and analysis of electricity market price modelling. Together with this chapter, it will complete the GENCO's side bidding and risk management research in this thesis.

Chapter 8

Assessing the Risks of Electricity Trading

In the previous chapters, strategic bidding mechanism and price modelling methodologies have been presented. These frameworks and methodologies provide useful tools for GENCO's operation in an electricity market. As discussed earlier, price modelling is a key functionality required for both the GENCO and ISO. In this chapter, a detailed risk assessment method is presented to study the impact of volatility of spot price on the risks of a GENCO. A framework is also proposed for assessing the market risk exposure of a given portfolio for a GENCO. To further the price modelling work presented in previous chapters, in this framework, a mean-reverting jump-diffusion model is employed to model the spot price and a nonlinear regression technique is proposed to model the relationship between spot price and relevant factors. The risk neutral process of the spot price is also developed and presented in this chapter. Finally Value at Risk and stress testing methods are employed to quantify the market risk exposure of a given portfolio with detailed case studies. This chapter completes the coverage of GENCOs bidding and associated risk management practices in a deregulated electricity market.

8.1 Introduction

As studied in earlier chapters, among all challenges in a deregulated electricity market, the strong volatility of the spot price remains one of the most significant challenges in the market. This strong volatility is caused by the unique characteristics of electricity, such as non-storability and inelastic demand. Unrestricted exposure to spot price risks can lead to severe consequences. In February 2004, the high prices in Texas during a 3-day ice storm caused the bankruptcy of an electricity retailer which was exposed to spot market prices. In the Australian market, the price spike can be as high as 9,000$/MWh, while the spot price is usually 40-50$/MWh under normal circumstances over most of the time. The significant market risks have given rise to a variety of electricity financial instruments and stimulated strong interests in effective risk management techniques.

In the past, extensive research has been conducted on electricity market risk management. Prior to the deregulation, several risk sources have been identified and a review of these risk sources is given in [140]. The work in this chapter evaluates different risk management techniques in an integrated resource-planning context, focusing on the flexibility and robustness of the different strategies.

In the deregulated market, the spot price risk is widely recognized as an important issue to address. Forward/futures contracts are widely used as financial instruments to hedge the spot price risk. It is therefore an interesting problem to study how to construct an appropriate portfolio of spot electricity and futures/forward contracts. The authors of [141] propose a model of financial risk management and use the concept of efficient frontier to illustrate the trade-off between profit and risk. In [142], the optimal generation portfolio is constructed by employing a utility function to achieve a reasonable profit-risk trade-off.

Besides forward and futures contracts, other financial derivatives have also been introduced to meet the needs of market participants. These derivatives include vanilla options and exotic options like spark spread options, swing options and swaptions [143-147]. These derivatives are currently actively traded in both exchanges and over-the-counter (OTC) markets. The number of papers concerning the valuation of electricity derivatives is still scarce. Most of the existing research on electricity derivatives pricing employ the widely-used mathematical financial models like Black-Scholes models and Geometric Brownian motion [148]. Some papers have also paid attention to the special characteristics of electricity. For example, some papers argue that the model of electricity prices should incorporate time-changing volatility and the possibility of jumps in prices [143, 146, 149]. Others on the contrary, emphasize the importance of modelling the seasonal patterns of electricity prices and its mean reversion [147]. Other models used to model spot prices include GARCH and its variants [150, 151] and Markov regime switching model [152]. There are also models proposed for direct modelling of electricity forward curves [153, 154].

In this chapter, a comprehensive framework is presented to assess the market risk exposure of a given portfolio. In the proposed approach, a mean-reverting jump-diffusion model is employed to model the spot electricity price. This approach is different from that of Chapter 7 where the forecast relays on artificial intelligence methods. To better capture the predictable component of the spot price, a nonlinear regression technique is introduced to model the relationship between the spot price and its relevant factors such as demand and supply. Moreover, the periodic behaviour of the electricity price caused by the seasonal variation of temperature will also be taken into account. The maximum likelihood estimator of the model will be derived and DE will be employed to estimate model parameters.

Based on the proposed spot price model, the corresponding risk-neutral process of the spot price can also be obtained. Any electricity derivatives can then be valued as the expected value, under risk neutral distribution, of its payoffs discounted to the valuation date with the risk-free interest rate. The proposed framework can therefore incorporate any electricity derivatives into the risk assessment.

The proposed framework uses *Value-at-risk* (VaR) and stress testing to quantify the market risk exposure of a given portfolio. VaR is the worst loss of a portfolio at a specified confidence level. It measures the total portfolio risk and takes into account the portfolio diversification and leverage. Since VaR only measures the downside risk of a portfolio under normal market conditions, the stress testing, which calculates the potential loss under extreme market conditions, is employed to complement VaR and give a comprehensive measurement of the market risk.

The rest of this chapter is organized as follows: Section 8.2 briefly introduces the ideas of the proposed risk management framework. Section 8.3 discusses the spot price model, the derivatives pricing approach and the kernel regression technique in more details. In Section 8.4, comprehensive case studies are conducted to verify the effectiveness of the proposed approach.

8.2 Overview of the Proposed Framework

In practice, the most important step of risk management is to quantify the risk exposure of a portfolio. The risk manager will then take necessary actions based on the estimated risk and the risk management policies of the company. A framework to assess the risk of electricity trading is proposed in this chapter. In this section the main procedure of the framework is briefly introduced. The main idea of the framework is to construct the spot price model based on the historical market data, then value the given portfolio based on the estimated model. Monte Carlo simulation will be employed to generate different spot price paths and based on which the VaR of the portfolio can be calculated. The procedure of the framework is given as follows:

(1) Model estimation

Given a specific spot price model, its parameters are firstly estimated from the historical data. The risk neutral process is then obtained based on the estimated model.

(2) Generate a price path

A spot price series will be generated based on the model estimated from step (1). The valuation of the portfolio will be based on the randomly generated spot price path.

(3) Value the given portfolio

All the positions in the given portfolio will be valued according to the price path generated in step (2). These positions can be the power traded in spot market, and any types of derivatives.

(4) Repeat (2) and (3) for *N* times, where *N* is the number of the iterations of the Monte Carlo simulation.

(5) Based on the *N* estimated values of the portfolio, obtain its VaR.

(6) Perform the stress testing to obtain the potential maximum loss under extreme market conditions.

The basic procedure of the proposed framework is illustrated in Fig. 8-1. We will conduct several case studies to demonstrate that it is effective.

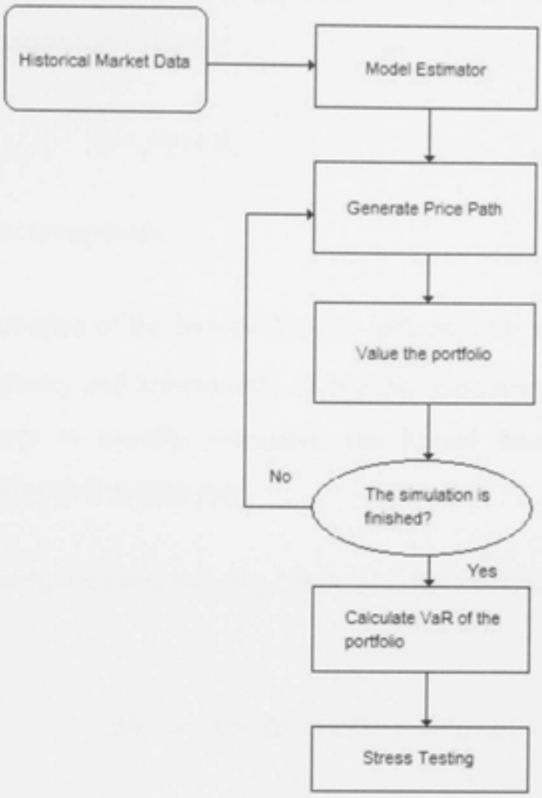

Figure 8-1 The Proposed Risk Management Framework

8.3 The Proposed Risk Management Approach

In this section, the details of the proposed approach of electricity trading risk assessment will be introduced first. The spot price model is firstly introduced. The risk neutral process based on the proposed spot price model will also be presented. Subsequently, how to value the electricity derivatives based on the proposed model will be given. Two approaches, VaR and stress testing, of risk measurement will be introduced. Since in the proposed approach, the kernel based regression and differential evolution algorithm will be employed, we finally give brief introductions to these two methods.

8.3.1 Modelling the Spot Market Price

The electricity price in the spot market is assumed to follow a stochastic process which has two components. The first component is considered to be deterministic, while the second one is assumed to follow a jump augmented diffusion process. The spot price Y_t can therefore be expressed as follows:

$$Y_t = f(t) + S_t \tag{8.1}$$

, where S_t is the random component.

In practice, $f(t)$ is a function of the factors that can influence the electricity price, such as load, generation capacity and temperature. Since the relationship between the price and its relevant factors is usually nonlinear, the kernel based regression [154] technique is used to estimate function $f(t)$.

In this proposed approach, the random component S_t is assumed to follow a process of the form:

$$dS_t = -kS_t dt + \sigma dX + Jd\pi(\phi) \tag{8.2}$$

where $k > 0$, σ represents the volatility of the process, and dX is the variation of a standard Brownian motion. $\pi(\phi)$ represents a Poisson counting process [155] with mean ϕ; J is the jump size, which follows a normal distribution $N(\mu, \delta^2)$. Therefore, equation (8.2) essentially represents a mean reverting jump-diffusion process with a zero long-run mean and a mean reversion rate of k. The occurrences of jumps are governed by $\pi(\phi)$. Following the common practices of financial modelling, we assume that the Brownian motion X, the Poisson process $\pi(\phi)$ and the jump size J are independent from each other.

From Eq. (8.1), we have $S_t = Y_t - f(t)$, substitute it into (8.2) we have:

$$d(Y_t - f(t)) = -k(Y_t - f(t))dt + \sigma dX + Jd\pi(\phi) \tag{8.3}$$

Equation (8.3) shows that if Y_t is greater than $f(t)$, it will move down on average, while on the other hand it will rise on average. In the long run Y_t converges to $f(t)$. Note that the only uncertainties of the model come from three sources dX, $d\pi(\phi)$ and J.

To value the electricity derivatives, a powerful approach is the risk-neutral pricing [156]. Generally speaking, risk-neutral pricing assumes that electricity financial markets are risk-neutral. All financial instruments will therefore yield an identical return of the risk free interest rate. Theoretically the risk-neutral assumption is equivalent to the no arbitrage assumption. In electricity markets however, the non-storability of the electricity weakens the non-arbitrage assumption. The market price of risk [144] should therefore be introduced to adjust the drift rate of the risk-neutral process. Following the approach used in [157], the adjusted risk-neutral process can be given as:

$$dS_t = k(\frac{-\lambda\sigma}{k} - S_t)dt + \sigma dX + Jd\pi(\phi) \tag{8.4}$$

where λ is the market price of risk, which can be estimated from the historical data [144].

The statistical properties of S_t can be analysed by deriving the characteristic function. For a time interval [0, T], the characteristic function $F(S,T;w)$ [158] can be obtained by solving the Kolmogorov backward equation (KBE):

$$k(\frac{-\lambda\sigma}{k} - S)\frac{\partial F}{\partial S} + \frac{1}{2}\frac{\partial^2 F}{\partial S^2}\sigma^2 - \frac{\partial F}{\partial T} + \phi E[F(S+J) - F(S)] = 0 \tag{8.5}$$

with the boundary condition $F(S,T=0;w) = e^{jwS}$. Here $j = \sqrt{-1}$ and w is the characteristic function parameter. As proved in [158], the solution to (8.5) is:

$$F(S,T;w) = e^{\alpha(T;w)+S\beta(T;w)} \tag{8.6}$$

$$\alpha(T;w) = \int((-\lambda\sigma\beta(T;w) + \frac{1}{2}\sigma^2\beta^2(T;w) + \phi E[e^{J\beta(T;w)} - 1])dT \tag{8.7}$$

$$\beta(T;w) = jwe^{-kT} \tag{8.8}$$

Then the n^{th} moment of S_t can be obtained by differentiate $F(S,T;w)$ with respect to w for n times when $w=0$. The conditional mean of S_t can therefore be calculated as:

$$E_0[S_t] = (-\frac{\lambda\sigma}{k} + \frac{\phi\mu}{k})(1-e^{-kt}) + S_0e^{-kt} \tag{8.9}$$

Considering $S_t = Y_t - f(t)$, we finally obtain the conditional mean of the spot price:

$$E_0[Y_t] = f(t) + (-\frac{\lambda\sigma}{k} + \frac{\phi\mu}{k})(1-e^{-kt}) + (Y_0 - f(0))e^{-kt} \tag{8.10}$$

8.3.2 Price Model Parameter Estimation

The *Maximum Likelihood Estimation* (MLE) method will be employed to estimate the model parameters. Assume that a series of spot electricity prices $\{\hat{Y}_t\}, t = 1..T$ has been observed, and we can estimate $\{\hat{f}(t)\}, t = 1..T$ with the kernel regression technique discussed in the following sections. We can then obtain a series of observations of process (8.2):

$$\hat{S}_t = \hat{Y}_t - \hat{f}(t) \tag{8.11}$$

The discrete form of process (8.2) can be derived as follows:

$$S_t - S_{t-1} = -kS_{t-1} + \varepsilon + (\pi(t;\phi) - \pi(t-1;\phi))J \tag{8.12}$$

$$\varepsilon \sim N(0, \sigma^2) \tag{8.13}$$

From (8.12) we can see that the conditional probability density of S_t is the sum of a n ormal and a Poisson distribution. To obtain the ML estimator of model (8.12)-(8.13), we assume that at most one price jump can occur in each time interval $[t, t+1]$. This assumption is reasonable for high frequency data, e.g. data at daily frequency [158]. Based on our assumption, the occurrence probability of price jumps in a given time in terval can then be well approximated with a Bernoulli distribution with parameter ϕ. The proof of using Bernoulli approximation of Poisson distribution can be found in [1 58]. Based on the Bernoulli approximation, the conditional density of S_t will follow a normal distribution, since both the noise ε and jump size J are normally distributed.

If a price jump occurs in a time interval $[t, t+1]$, the conditional density of S_t will be:

$$P_1[S_t \mid S_{t-1}] = \frac{1}{\sqrt{2\pi(\sigma^2 + \delta^2)}} e^{-\frac{(S_t - S_{t-1} + kS_{t-1} - \mu)^2}{2(\sigma^2 + \delta^2)}} \tag{8.14}$$

Similarly, if no price jump occurs, the conditional density will be:

$$P_0[S_t \mid S_{t-1}] = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(S_t - S_{t-1} + kS_{t-1})^2}{2\sigma^2}} \tag{8.15}$$

Then the overall conditional density of S_t can be given as the weighted sum of P_1 and P_0:

$$P[S_t \mid S_{t-1}] = \phi P_1 + (1-\phi)P_0 \tag{8.16}$$

It should be noted that $P[S_t \mid S_{t-1}]$ is also normally distributed because it is a linear combination of normal distributions.

Following the common practices of financial modelling, we assume that S_t is a Markov process [159]. Therefore, S_t is only determined by the information available at time $t-1$. In other words, observations before time $t-1$ will not help to improve forecasts. Under this assumption and according to the Bayes theorem, the conditional density of S_t over the time interval $[0,T]$ can be given as:

$$P[S_T \mid S_0] = \prod_{t=1}^{T} P[S_t \mid S_{t-1}] \tag{8.17}$$

The conditional likelihood function is derived as:

$$L(\vec{\theta}; \{\hat{S}_t\}) = \prod_{t=1}^{T} P[\hat{S}_t \mid \hat{S}_{t-1}] \tag{8.18}$$

where $\vec{\theta} = (k, \sigma, \mu, \delta, \phi)'$ is the parameters to be estimated. The ML estimates of $\vec{\theta}$ are the values that maximize (8.18).

8.3.3 Valuing the Electricity Portfolio

The essential step of risk management is to estimate the value of a given portfolio. According to the risk neutral pricing theory, all derivatives should be valued at their expected payoffs discounted with the risk free interest rate. In this chapter, it is assumed that the risk free interest rate is constant. Since the proposed framework is based on the risk neutral process derived in Section 8.3.1, it is very flexible in that any electricity derivatives, whose underlying is spot electricity, can be easily handled. Moreover, the spot price model can also be replaced with other spot models, which can lead to risk-neutral processes.

Many different derivatives can be traded in global electricity markets. In this chapter the *Australian NEM* is selected for case studies. At this stage, only the valuation problems of two widely-used derivatives are studied, namely swap and cap. Other derivatives can be future work.

The *swap* [144] is the simplest and most commonly-traded forward contract in the Australian market. The swap in the Australian market can be traded both in the exchange and OTC market. Generally speaking, an electricity swap is an agreement for the exchange of the right to settle a specific notional quantity of electric energy (in MWh) at a fixed price for a contract for the right to settle the same quantity of electric energy at a floating price. The fixed price is agreed by the two counterparties. The floating price on the other hand is usually the spot market price. For each half an hour of the duration of the swap, the fixed price payer (long position) pays the fixed (strike) price multiplied by the notional amount of the swap for that period. In return, the fixed price receiver (short position) pays the spot price multiplied by the notional amount. Therefore, the fixed price payer essentially receives the difference between the spot price and the strike price. If we denote the strike price of the swap as F_0, assume that the notional quantity of the swap is Q MW in each half an hour period, and the swap has a duration of T half-hour periods; the payoff of a long position of the swap can then be given mathematically as:

$$P = \sum_{t=1}^{T} (Y_t - F_0) \times \frac{Q}{2} \tag{8.19}$$

An electricity cap is essentially a call option where the buyer has the right but not the obligation to buy the electricity at the strike price. If the pool price turns out to be greater than the strike price, the cap will be exercised automatically and the owner of the cap will obtain a cash settlement equal to the difference between the strike price and spot price. Otherwise the cap will not be exercised and no cash flow is generated. A standardized cap with a strike of 300 \$/MWh is traded in the Sydney futures exchange. Assume that the cap has a notional quantify of Q MW in each half an hour period, and has a duration of T half-hour periods, the payoff of the cap can then be given as:

$$P = \sum_{t=1}^{T} \max(Y_t - 300, 0) \times \frac{Q}{2} \tag{8.20}$$

Based on the risk neutral process (8.4), the value of a swap at time $t = 0$ can be calculated as:

$$\begin{aligned} V &= e^{-rT} E_0\left[\sum_{t=1}^{T} (Y_t - F_0) \times \frac{Q}{2}\right] \\ &= \frac{e^{-rT} \times Q}{2} \times \left(\sum_{t=1}^{T} E_0[Y_t] - T \times F_0\right) \end{aligned} \tag{8.21}$$

Substituting (8.10) into (8.21) we can obtain the closed form solution of the swap value.

It is difficult to derive the closed-form solution for the cap, we can however employ simulation based approach to compute its value. The procedure is as follows:

(1) Generate a simulated price series $Y_t, t = 1 \ldots T$;

(2) Calculate the simulated cap payoff $P^{(1)}$ for the first iteration based on the Equation (8.20);

(3) Repeat steps (1) and (2) for N iterations and obtain $P^{(1)} \ldots P^{(N)}$.

(4) The cap value can then be calculated as:

$$V = e^{-rT} \times \frac{\sum_{i=1}^{N} P^{(i)}}{N} \tag{8.22}$$

8.3.4 Value at Risk and Stress Testing

Value at Risk (VAR) is the primary measure of market risk exposure of a portfolio in practice. VaR is a summary measure of the downside risk, expressed in dollars. Generally speaking, VaR is defined as the maximum loss over a target horizon such that there is a low, pre-specified probability that the actual loss will be greater [160].

In the proposed approach, the procedure of calculating VaR of a given portfolio can be summarized as:

(1) Input the confidence level α, horizon T of VaR, and the iteration number N of the Monte Carlo simulation.

(2) Based on the spot price model (8.1), (8.2) and (8.9), generate a simulated price series $Y_t, t = 1 \ldots T$;

(3) Employ the approaches described in Section 8.3.2 to calculate the values of each position in the given portfolio, and sum the values to get the total portfolio value $V^{(1)}$;

(4) Repeat steps (2) and (3) for N times and obtain the simulated portfolio values $V^{(1)}, \ldots V^{(N)}$;

(5) Sort $V^{(1)},...V^{(N)}$ in the ascending order, select the $\frac{\alpha \times N}{100}$ th and $\frac{N}{2}$ th simulated portfolio values. The VaR is then the difference between the two values.

VaR is insufficient to measure the worst ever loss that could happen. *Stress testing* [160] should therefore be conducted to complement. Stress testing aims at identifying situations that could create extraordinary losses for the portfolio. In the electricity market, possible stress testing scenarios may include extreme price spike, negative price, system congestion and major system outage. The impacts of these extreme events on the portfolio should be evaluated.

8.3.5 Kernel Based Regression

Kernel Based Regression [154] is a class of algorithms for regression analysis, whose best known element is the SVM. Kernel based regression approach solves the problem by mapping the data into a high dimensional feature space, where each co-ordinate corresponds to one feature of the data items, transforming the data into a set of points in a Euclidean space. In that space, a variety of methods can be used to find relations in the data. Since the mapping can be quite general (not necessarily linear, for example), the relations found in this way are accordingly very general. This approach is called the kernel trick.

Kernel methods owe their name to the use of kernel functions, which enable them to operate in the feature space without ever computing the coordinates of the data in that space, but rather by simply computing the inner products between the images of all pairs of data in the feature space. This operation is often computationally cheaper than the explicit computation of the coordinates. Kernel functions have been introduced for sequence data, graphs, text, images, as well as vectors.

Algorithms which are capable of operating with kernels include SVM, *Partial Least Square*, *Ridge Regression*, and many others. Because of the particular culture of the research community that has been developing this approach since the mid-1990s, most kernel algorithms are based on convex optimization or eigenproblems, are computationally efficient and statistically well-founded. Typically, their statistical properties are analysed using statistical learning theory. In this study, the kernel based least square [154] method will be employed to estimate the relationship between the spot price and its relevant factors.

8.4 Case Studies

In this study, the historical contract price data of Australian market are selected to evaluate the performance of the proposed approach. The model generated swap and cap prices will firstly be compared with the historical prices to verify that the proposed contract pricing approach is effective.

The authors firstly compare the actual forward curves of the first three quarters of 2008 with the forward prices given by the proposed model. The characteristics, including mean, standard deviation (SD), and maximum (MAX) of the swap price data are given in Table 8-1:

Table 8-1 The Characteristics of the Swap Price Data

	Q1 2008			Q2 2008			Q3 2008		
	Mean	**SD**	**Max**	**Mean**	**SD**	**Max**	**Mean**	**SD**	**Max**
Peak	127.04	18.23	163	74.76	23.8	125	72.05	15.88	124
Off-Peak	32.28	4.02	40.5	34.86	7.27	48	34.49	6.96	44.75
Flat	73.34	8.74	87.7	51.85	14.07	78.58	51.07	10.3	79.47

The model generated forward curves are given in Figs 8-2 – 8-10.

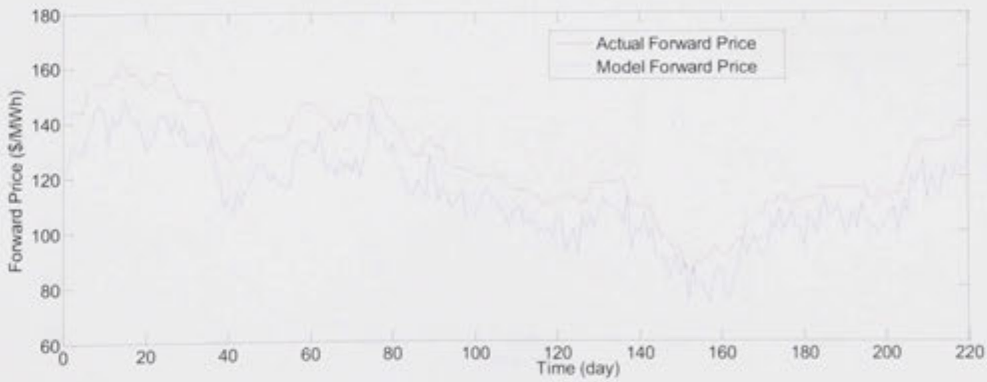

Figure 8-2 Model Generated Forward Prices for Quarter 1 2008 – Peak Load

Figure 8-3 Model Generated Forward Prices for Quarter 1 2008 – Off-peak Load

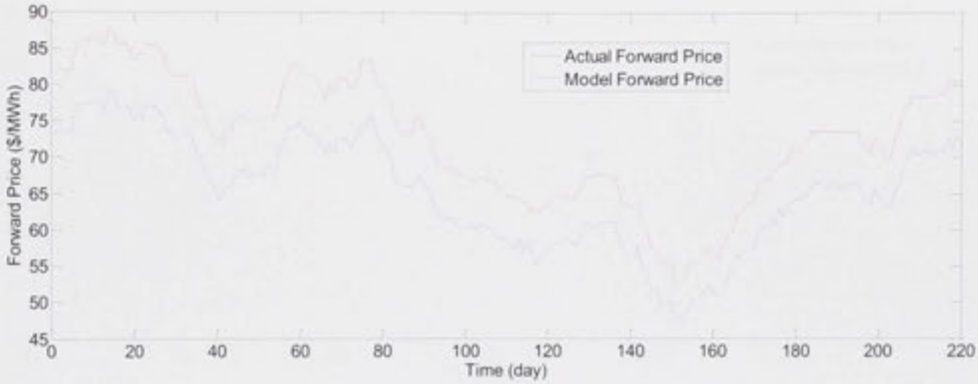

Figure 8-4 Model Generated Forward Prices for Quarter 1 2008 – Flat

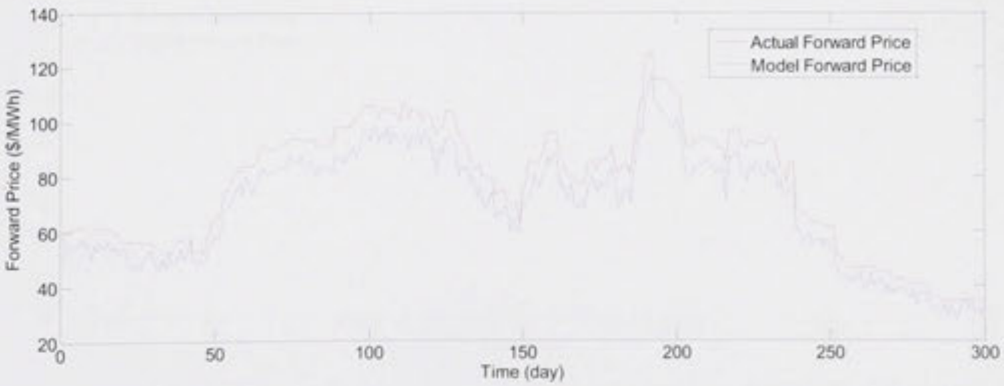

Figure 8-5 Model Generated Forward Prices for Quarter 2 2008 – Peak Load

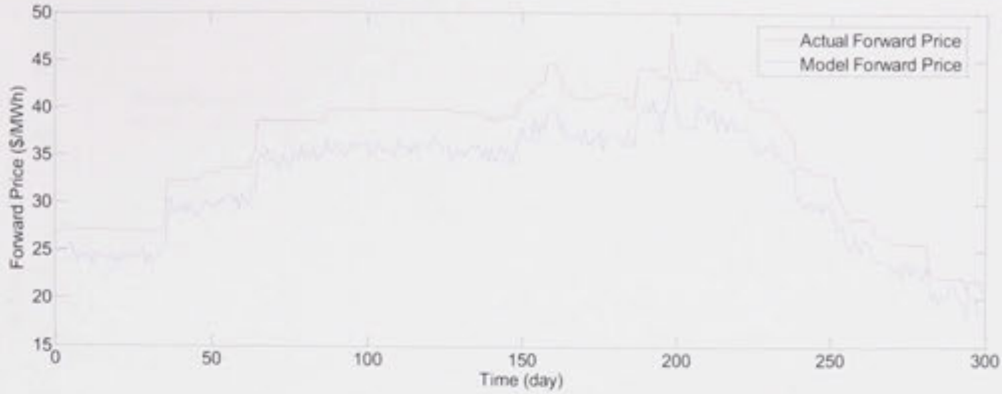

Figure 8-6 Model Generated Forward Prices for Quarter 2 2008 – Off-peak Load

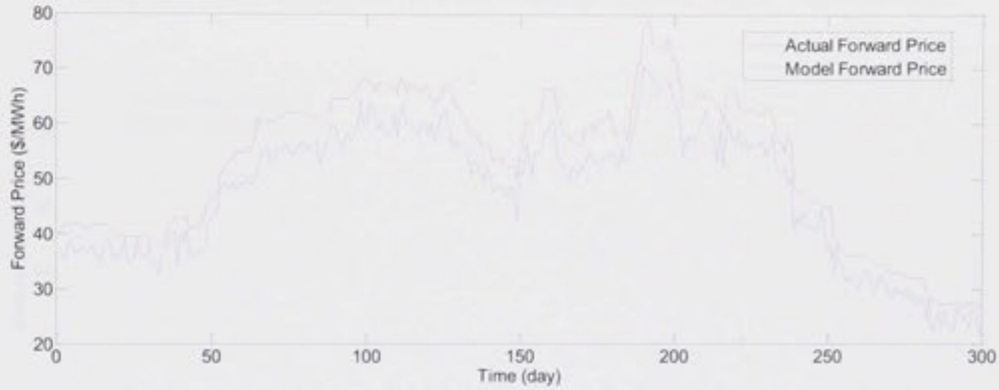

Figure 8-7 Model Generated Forward Prices for Quarter 2 2008 – Flat

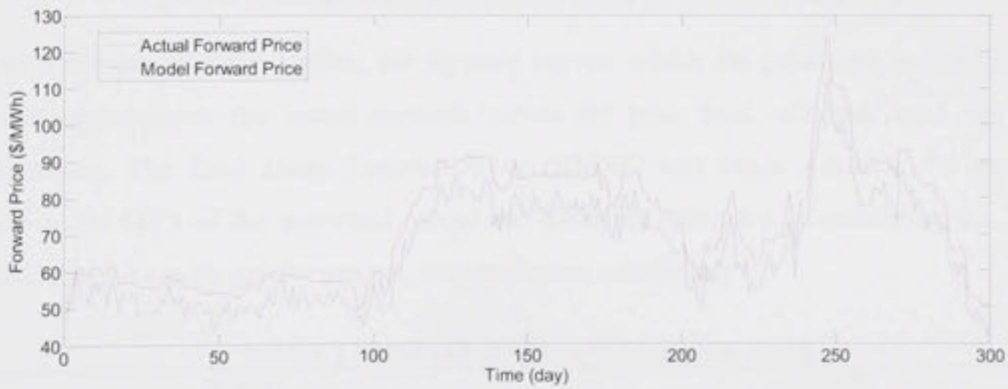

Figure 8-8 Model Generated Forward Prices for Quarter 3 2008 – Peak Load

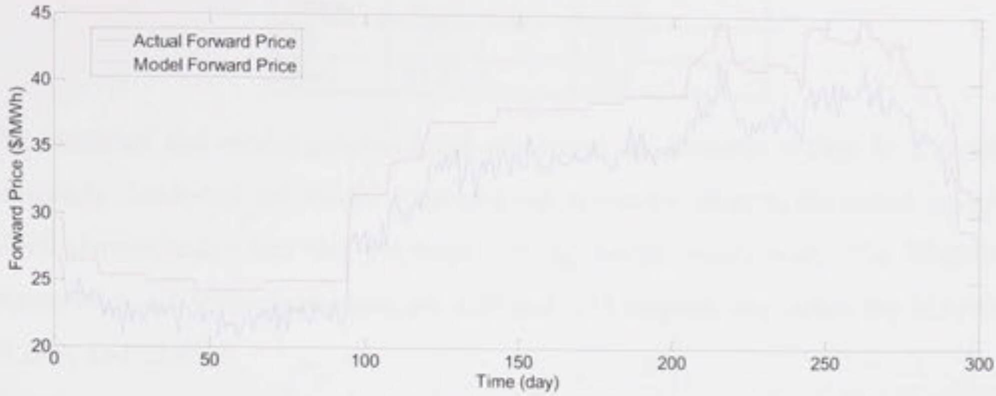

Figure 8-9 Model Generated Forward Prices for Quarter 3 2008 – Off-peak Load

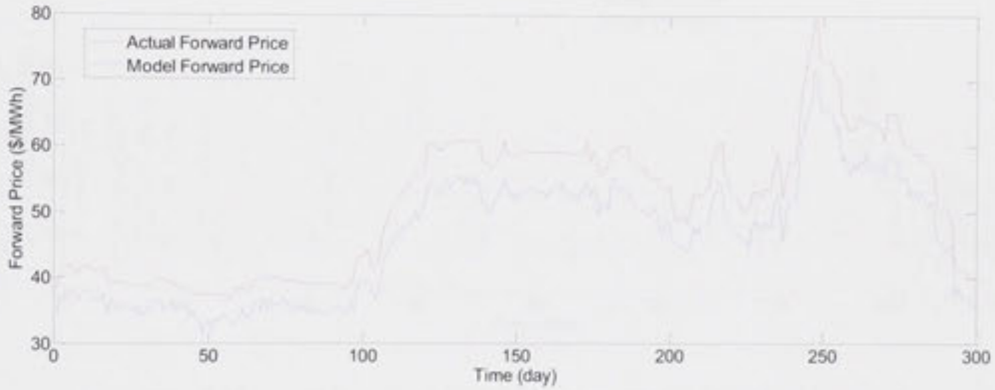

Figure 8-10 Model Generated Forward Prices for Quarter 3 2008 – Flat

As is shown in above figures, the forward curves, which are generated by the model, well approximate the actual forward curves for peak load, off-peak load and flat contracts. The *Root Mean Squared Error* (RMSE) and *Mean Absolute Percentage Error* (MAPE) of the proposed model are given in Table 8-2. Considering the high volatility of the electricity market, the results are satisfactory.

Table 8-2 RMSE and MAPE of The Proposed Model

RMSE					*MAPE*			
	Q1 2008	**Q2 2008**	**Q3 2008**			**Q1 2008**	**Q2 2008**	**Q3 2008**
Peak	13.2886	8.0709	7.591		**Peak**	14.78%	12.33%	10.88%
Off-peak	3.2628	3.5948	3.5798		**Off-Peak**	7.55%	6.98%	7.86%
Flat	7.3847	5.6326	5.3036		**Flat**	9.06%	9.22%	9.16%

In order to further test the effectiveness of the proposed model, the model generated cap prices are compared with the actual cap prices. The historical cap prices of the Victoria and Queensland markets for quarter 1, 2009 are selected. The characteristics of the data are given in Table 8-3.

Table 8-3 The Characteristics of 2009 Q1 Cap Prices

	VIC market	QLD market
Mean	10.19	18.16
SD	7.87	11.62
Max	40.25	55.5

The historical and model generated cap premiums are depicted in Figs 8-11 and 8-12. As clearly illustrated, the model generated cap prices are close to the actual cap prices, which demonstrates that the proposed pricing model works well. The RMSEs for Queensland and Victoria markets are 4.29 and 2.71 respectively, while the MAPEs are 19.29% and 22.02%.

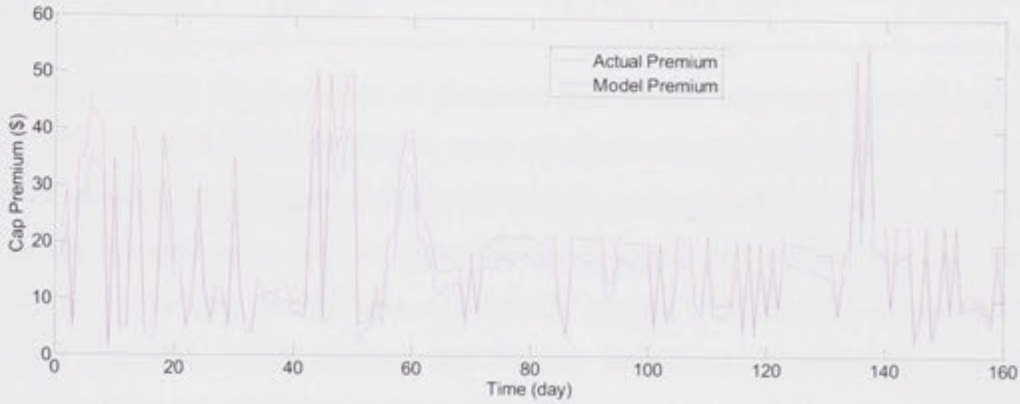

Figure 8-11 Actual Premium v.s. Model Premium for QLD Flat Contract

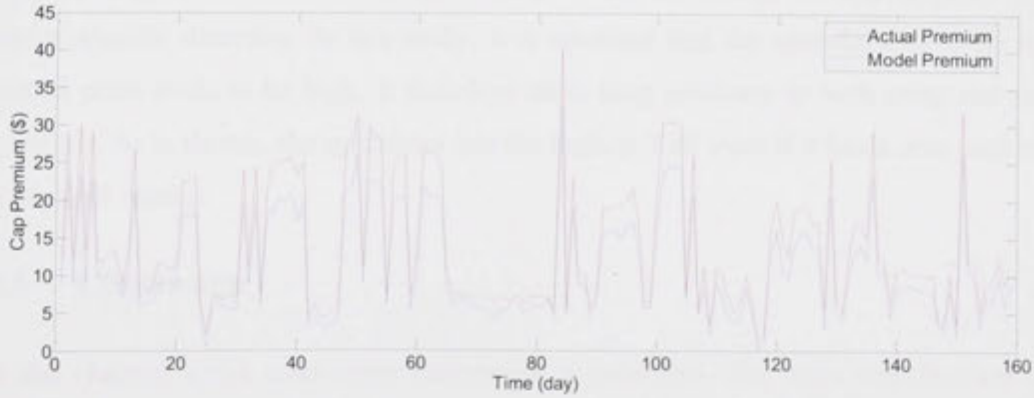

Figure 8-12 Actual Premium v.s. Model Premium for VIC Flat Contract

To further investigate the performance of the proposed framework, this model is employed to estimate the VaR of five different portfolios. The horizons of risk assessment for the five portfolios are all set as from January 1st 2008 to March 31st 2008. The risk free interest rate is assumed to be a fixed value of 7%. The definitions of the five portfolios are given in the Table 8-4. The positive symbol (+) denotes a long position while the negative (-) denotes a short position. It is assumed that the swap and cap are all Queensland flat contracts.

Table 8-4 The Definitions of The Five Portfolios in The Proposed Framework

	Generator	Hedged Generator	Retailor	Hedged Retailor	Speculator
Spot Market	-6480 MWh	-6480MWh	+6480MWh	+6480MWh	0
Swap	0	-1000MWh	0	+1000MWh	+1000MWh
$300 Cap	0	0	0	+500MWh	+500MWh

The VaRs of the five portfolios are shown in Table 8-5:

Table 8-5 The VaRs of The Five Portfolios

Portfolio	Generator	Hedged Generator	Retailor	Hedged Retailor	Speculator
VaR ($)	763,710	278,640	763,710	502,890	978,340

In the simulation, the portfolios of generator and retailer only have positions in the spot market, which indicates that they have unhedged exposure to the spot market risk. On the contrary, the hedged generator and hedged retailer portfolios use swap and cap to hedge the spot price risk. As expected, the generator and retailer that only have positions in the spot market have significantly greater VaR than the corresponding hedged portfolios, which indicates that the two derivatives effectively decrease the exposure of the two portfolios to the market risk.

A special case is the speculator portfolio. The speculator does not employ derivatives for risk mitigation. On the contrary, it earns money by betting the market price will take a specific direction. In this study, it is assumed that the speculator predicts the market price tends to be high. It therefore takes long positions in both swap and cap contracts. As is shown, the speculator has the highest VaR even if it has a zero position in the spot market.

8.5 Conclusion

In this chapter, a risk assessment framework is presented. The main contributions of this chapter include:

(1) A comprehensive framework to assess the market risk exposure of a given portfolio. A mean-reverting jump-diffusion model is employed to model the spot electricity price, and a nonlinear regression technique is introduced to model the relationship between the spot price and relevant factors. Temperature impact on price is also considered in the framework;

(2) Development of the capability of the framework to incorporate any electricity derivatives on a risk neural distribution in its risk assessment process; and

(3) Value-at-risk (VaR) and stress testing based methods are developed as part of the framework to quantify the market risk exposure of a given portfolio. They altogether are able to give a comprehensive measurement of the market risk needed for the GENCO.

It should be noted that the tool presented in this chapter completes the package of framework for GENCO risk management including strategic bidding and optimal portfolio selection. This chapter thus concludes the major contributions of this thesis. In the next chapter, conclusions and future work will be given.

Chapter 9

Conclusion and Future Work

9.1 Conclusions

This thesis reported the research findings of two main research problems and proposed corresponding solution methodologies, namely, generation strategic bidding and generation portfolio optimisation in an electricity market. These problems are basically optimisation problems; as such, a comprehensive overview of multi-objective optimisation problem formulation and algorithms are given in the thesis to form a mathematical foundation for various optimisation tasks involved. Electricity price forecasting is the key market signal in risk management for generators; and operations and planning for ISO. A novel price forecasting method is proposed in the thesis as well; it also provides a bridge between the two main research problems. Moreover, comprehensive approaches are also proposed for managing the risks of electricity trading.

Firstly, a comprehensive review of generation bidding strategies is given, followed by detailed discussions on optimisation formulation and algorithms. The complexity of various optimisation problems through out the thesis requires advanced numerical methods. In this research, the following methods are investigated and utilised:

- GA is the most widely used evolutionary algorithm with clear structures and distinct operators representing the natural evolution process in its search and optimisation process. GA is used in forming the framework of optimal bidding strategy with market uncertainties in the thesis.
- Monte Carlo simulation, which is used widely in practice to obtain statistical information of a complex problem so as to assist the decision making process. It is particularly useful if the problem investigated can not be represented in an analytical form which can be studied by a deterministic approach. In this thesis,

Monte Carlo simulation approach is used to obtain the optimal bidding strategies for a GENCO with only incomplete information from its rivals and the market.

- DE, which is a relatively new evolutionary algorithm featured by structural simplicity and relatively higher computational efficiency. DE is used in the optimal portfolio selection process in Chapter 6 of the thesis.
- FIA, as a new heuristic optimisation algorithm with better global search capabilities is used to build market clearing forecast model in the thesis.

Other techniques used in the thesis include SVM and GARCH model to obtain optimal bidding strategies.

In order to build optimal bidding strategies, two challenges have to be handled properly, namely, market uncertainties and incomplete information of rival generators in the market. Chapters 4-5 present a framework of optimal strategic bidding for generators considering such challenges. The framework presented in Chapter 4 involves the following main steps:

- Forecasting demand and price in the market;
- Quantification of market uncertainties with data mining and statistical methods ;
- Construction of bidding scenarios based on the results obtained in previous steps;
- Optimisation of generator self-scheduling plans; and
- Construction of bidding curves for each bidding scenarios.

In Chapter 5, this process is further enhanced by a method to calculate MCP through its correlation with generators' bidding quantities in the market.

For a generator, in addition to revenue obtained from spot market, it also uses other financial instruments to hedge the risks and maximise its return by selecting its portfolio in an optimal way. There are two major challenges to construct the optimal portfolio:

- Generators' portfolio selection consists of many factors and it is difficult to develop a unified model for different markets and contracts;
- The selected portfolio is optimal only in the theoretical sense. Its performance largely depends on accurately estimating the probability distributions of the returns of different markets and contracts.

To address all these issues, a novel portfolio selection approach is proposed in Chapter 6. It can be used for GENCOs to allocating its generation capacities in different markets and using contracts for risk management. The optimal portfolio is selected by optimising a utility function composed of portfolio return and risks. The proposed approach is applicable for handling different available assets in the electricity market. Moreover, it is able to provide better estimates of the distributions of asset returns by employing advanced statistical and econometrics methods.

In all the methodologies proposed, MCP forecast is used through out. How to accurately forecast the MCP largely affects the performance of the propose bidding and portfolio selection methods. In Chapter 7, a new forecasting method is presented for price forecasting purpose. An advanced FIA based neural network model is developed to model and forecast the electricity price. It provides computational efficiency and accuracy in the forecasting process. It contributes to the overall methodology framework of generator bidding and portfolio selection approaches. These methods have been validated with realistic data from the Australian NEM.

For risk management purpose, MCP forecast alone is not sufficient. In order to have a rather comprehensive methodology, an effective risk assessment method and portfolio evaluation framework was given in Chapter 8. In this framework, a mean-reverting model is applied to model the spot price. The relationship between the spot price and relevant factors has been modelled by a nonlinear regression technique. The risk neutral process of the spot price is also developed and presented. Finally VaR and stress testing methods are employed to quantify the market risk exposure of a given portfolio. Detailed case studies have been given to further validate the effectiveness of the proposed method and framework.

Accordingly, the contributions of the thesis include

- Development of a general framework for generator strategic bidding in an electricity market;
- Development of methodologies to handle incomplete information in order to form more reliable and optimal bidding by generators in the market;
- Construction of a framework for generator optimal portfolio selection in order to maximise return while containing risks in the market;

- Development of an efficient price forecast model so as to form the basis for bidding and portfolio selection process; and
- Development of methodologies to enhance the risk management practices of the market participants.

Overall, this thesis provides a holistic view of generation risk management issues. It provides useful methodologies to meet the various challenges in an electricity market.

9.2 Future Work

Risk management for generators in an electricity market is a complex problem requires consideration of a variety of factors for different aspects. Although the thesis aims at providing a holistic view of generation risk management problem, however, there are further research topics identified though this research. The main topics for future work include the following:

- Challenges from environmental market schemes and *Carbon Pollution Reduction Scheme* (CPRS)

Generation sector is among those contributing the most to green house emissions. Consequently, the environmental market schemes have been introduced mainly targeting at the generation sector following the Kyoto protocol. The exact impact of environmental market schemes on the generation composition, profitability, dispatching order and generation new entry into the market is to be clearly depicted. However, it can be quite confidently anticipated that the generators in the Australian NEM will definitely be affected. There will be more renewable and combine cycle generators and less, if not completely no, coal fired power stations entering the market. Currently, the generation connection inquiries to the transmission network service providers by wind generators have been increasing rapidly in SA, VIC and TAS. Another important fact to be considered in this aspect is the CPRS promoted by the Australian government. On 27 April 2010, it had been announced that Government would not introduce the CPRS until after the end of the current commitment period of the Kyoto Protocol (which ends in 2012) and only when there is greater clarity on the actions of other major economies including the US, China and India. The government expects that CPRS can guarantee that Australia is to reduce its emissions to 25% of below 2000 levels by 2020 if the world agrees to a 450 parts per million CO2 target, otherwise a reduction of 5~15% below 2000 levels by 2020 is expected, [161]. The environmental market schemes and CPRS impact will have to be considered in forming optimal bidding strategies and selecting optimal portfolios by generators in the Australian NEM.

- *Distributed Generation* (DG) and its impact on GENCOs' bidding behaviour

DG in the Australian NEM grid has been increasing over the past few years. Although the current penetration has not reached a level so as to have evident impact on the spot market, however, with the environmental market schemes, CPRS and sustainable development vision, it is expected that more and more DG will be installed in the system. Consequently, they will have evident impact on the generation market when their penetration level is high enough. This forms another important future research topic.

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Appendix

The Australian National Electricity Market (NEM) consists of 5 interconnected regional markets including Queensland (QLD), New South Wales (NSW), Victoria (VIC), South Australia (SA) and Tasmania (TAS). The interconnectors of these regions and their geographic locations are shown below:

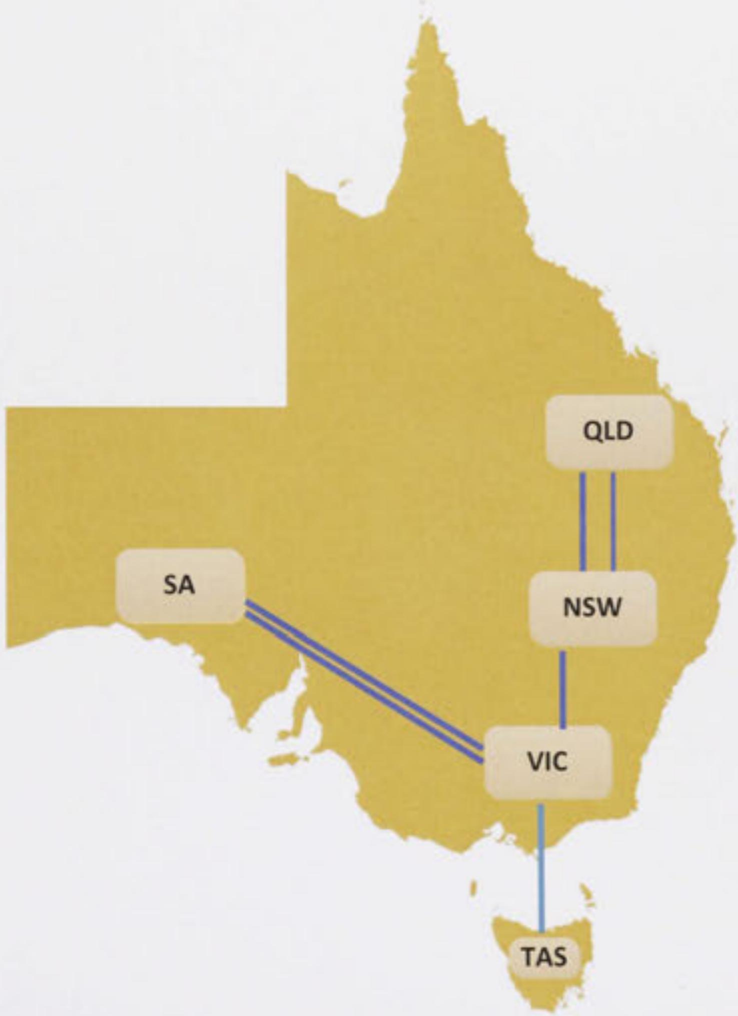

Figure A-1 Illustration of the Australian National Electricity Market