The Hong Kong Polytechnic University
Department of Electrical Engineering

ELECTRICITY MARKET ANALYSIS WITH CO-EVOLUTIONARY COMPUTATION

By

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Certificate of Originality

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ABSTRACT

The unique feature of the electricity power industry makes the power market more akin to an oligopoly. A great deal of work has been performed on analyzing power markets using the oligopoly models in the literatures. The Supply Function Equilibrium (SFE) and Cournot models have also been widely employed to model the electricity market. Many techniques, such as empirical analysis, agents-based simulation, iterative Nash Equilibrium (NE) search algorithms and complementarity program methods, have been utilized to determine the power market equilibrium. Despite of these previous efforts, no method is widely recognized as being an effective method for market equilibrium determination. Hence there is an urgent need to develop an effective and powerful approach for power market analysis and equilibrium determination.

Co-evolutionary computation is developed from traditional Evolutionary Algorithms (EAs), which simulates the co-evolutionary mechanism in nature and adopts the notion of ecosystem. It is a new methodology used to simulate the bidding behavior of the market players and to determine market equilibrium. The thesis applies co-evolutionary computation algorithms (CCAs) to solve the power market equilibrium and to study several important issues in power market analysis.

The first issue is that when transmission constraints are considered, the profit function of Generation Companies (GenCos) may be nonconcave and discontinuous with many local optima. Determination of market equilibrium becomes a more challenging task. A two-level evaluation process is developed in the thesis for the determination of the equilibrium. The Linear Supply Function Equilibrium (LSFE) and the Cournot market

models are employed and the market equilibrium is determined by CCA. The existence or non-existence of the NE due to the transmission and generation capacity constraints are illustrated using a 2-bus test system and the IEEE 30-bus system. The effects of different parameters settings of the LSFE model on the equilibria are also studied and compared with those found based on the Cournot model.

The second issue examined is to determine the market equilibrium in a multiple pricing period. When compared to actual markets, earlier research works study only a single pricing period market. A multiple pricing period market with inter-temporal constraints should also be studied to make the simulation results comparable to actual market settings. The CCA method used to study single pricing period market is then extended to multiple pricing period market analysis. It is found that the market outcome of a GenCo using a constant supply function across multiple pricing period is contrasted with the case that GenCos using a specified supply function in each pricing period. It is important to observe outcomes of different markets in which obligations for consistent bidding are set up or not.

Owing to the recent California electricity crisis, more and more researchers are convinced that forward market plays an important role for market power mitigated in electricity markets. In this thesis, the issue of whether rational GenCos would voluntarily enter forward markets or not is examined and the factors which could affect the bidding behavior are studied. The thesis formulates a two-settlement electricity market as a two-stage game. The LSFE model and Cournot model are used to model strategic bidding for the spot market, while the forward market is modeled by the

Cournot model. GenCos' bidding behaviors are analyzed by CCA and two numerical examples are used to verify the theoretical analysis.

From the works undertaken in this thesis, it is found that the CCA method is robust and flexible and has the potential to be used to solve the complicated equilibrium problems in real-world electricity markets.

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CHAPTER 1 INTRODUCTION

1.1 Electric Power Industry Deregulation

Power industry deregulation has taken place in many countries in the past twenty years. The earliest deregulation took place in Chile in the late 1970s. Argentina improved the Chilean model by imposing strict limits on market concentration and by improving the structure of payments. Then, the World Bank was active in introducing electricity markets in other Latin American nations, including Peru, Brazil and Colombia, during the 1990s. A key event for electricity markets occurred in 1990 when UK privatized the UK electricity supply industry. The process was used as a model for the deregulation of several other commonwealth countries, notably Australia and New Zealand.

In different deregulation processes, the institutions and market designs were often very different but underlying concepts were almost the same. These concepts are as follows: separate the contestable functions of generation and retail from the natural monopoly functions of transmission and distribution; establish a wholesale electricity market and a retail electricity market. The role of the wholesale market is to allow trading between generators, retailers and other financial intermediaries both for short-term delivery of electricity and for future delivery periods. A retail electricity market exists when end-use customers can choose their supplier from competing electricity retailers.

In fact, the wholesale and retail markets have been mixed (i.e. hybrid model) in many countries. Many regional markets have achieved some success and the ongoing trend continues to be towards deregulation and introduction of competition. However in 2000/2001 major failures, such as the California electricity crisis and the Enron debacle, caused a slow down in the pace of change and in some regions an increase in market regulation and reduction in competition. However, this trend is widely regarded as a temporary one against the longer term one towards more open and competitive markets.

1.2 Market Power

In this new environment, electricity is traded the same way as other commodities. However, a perfectly competitive market does not exist in practice. Many issues can contribute to the market inefficiency, such as market design flaws, market power, and inherent engineering features of power system operations [1]. Some characteristics of electricity markets facilitate the exercise of market power. These characteristics include inelastic demand, limited transmission capacity, and the requirement that supply and demand must balance continuously. Therefore, market power analysis has received attention in both theory and practice [2, 3]. It is important for market designers to fix flaws in market structure and for GenCos to be able to evaluate their positions and conduct their business.

Market power is the ability of a market participant to influence market characteristics (e.g. prices, market share, etc.) to advance its profitability. When applied to a liberalized electricity market, market power would mean the ability of a power company to raise prices and profit above the competitive market price level.

In the electricity supply business, market power normally exists to some extent irrespective of the market structure owing to the following reasons:

1. Electricity is an essential commodity of which reliable supply is depended upon for everyday living and business operation. This makes the short-term demand for electricity quite inelastic in response to price changes. Suppliers holding sizable market share can take advantage of this inelasticity to vary prices, where not regulated, without suffering from reduced sales volume and revenue.
2. In a competitive market where the price for electricity is largely determined by the supply/demand margin, suppliers having sizable market share can influence the short-term supply/demand margin to drive market price upward.
3. The electricity supply business is very capital intensive. Potential new participants often find it very difficult to enter an established market. Even when new generators can be built to compete for supplying existing or new customers, it is often impractical and cost prohibitive to replicate the power grid to deliver electricity to the end users. Lack of access to the power grid virtually blocks any potential new participants from competing with the incumbent suppliers that also own the grid.

Regulating market power and minimizing its abuse are therefore key considerations in ensuring proper market performance. Three types of market power are pertinent to the electricity market: the horizontal, vertical and locational market power.

1. Horizontal market power is exercised when an entity profitably drives up prices through its control of a single segment, such as electricity generation. An entity would possess horizontal market power when it owns a significant share of the total generating capacity available to the market.
2. Vertical market power is exercised when an entity involved in two related segments, such as electricity generation and transmission, uses its dominance in one segment to raise prices and earn extra profits for the overall enterprise or to disadvantage other suppliers.
3. Locational market power is the result of the existence of transmission constraint, which limits the ability for a region to access external supply sources. The local electricity suppliers may therefore charge the local customers a higher tariff without rivalry from external sources.

1.3 Market Power Assessing and Market Modeling

Market power is harmful to competition and it is necessary to identify the potential for its abuse, and such findings have important policy implications. In recent years, much research has been done on investigating the potential for market power abuse in electricity markets [4].

1.3.1 Market Power Assessing Index

Several indexes have been used to assess market power recently. The most widely used index for structural assessments of a market, the Herfindahl–Hirschman Index (HHI), is computed by squaring each supplier's market share, then adding the squared shares. Empirical research in electricity markets also sheds light on the level at which market concentration may have a significant adverse impact on the competitiveness. It is generally agreed that an electricity market composed of five equally sized GenCos would be workably competitive [5].

The HHI method has the advantage of specificity but the drawback that it has no supporting theory. Many researchers such as [6] have pointed out that structural measures of market power, such as the HHI, have several shortcomings when applied to electricity markets; the most obvious is that the demand elasticity is not represented in the HHI formulation. Certainly, the market power of a supplier will change over time as demand conditions change. When the demand increases, the market power of the suppliers will increase. The HHI also fails to consider a supplier's true competitive positions, since consideration of the relative costs of different generation resources or specific geographic factors is absent from the HHI [5].

The Lerner Index (LI) and Price–Cost Margin Index (PCMI) are other two retrospective indicators of market power [7, 8]. The former is defined as $LI = (p-MC)/p$ and the latter is defined as $PCMI = (p-p_c)/p_c$. Here, p, p_c and MC represent actual market price, perfectly competitive price and Marginal Cost (MC) respectively. Since it is hard to obtain MC information in a real market, these two indices do not have much practical value.

In fact, the market power depends not just on market concentration, but also on how demand varies relative to the degree of excess capacity. So another index, a forecast load and total available supply ratio (demand–supply ratio), is proposed in [7], and the New England market data is used to demonstrate it.

1.3.2 Analyzing Electricity Market by Economic Models

The following methods have been developed for market power analysis [4]: analysis of market shares and market concentration; estimation of pricing behavior; modeling market by economic models.

Most researchers focus on market power analysis by using economic models. Researchers have developed three directory branches for market modeling [9]: optimization models, equilibrium models and simulation models. Optimization models focus on the profit maximization problem for one of the GenCos competing in the market, while equilibrium models represent the overall market behavior taking into consideration competition among all participants. Equilibrium and simulation-based models represent market behavior considering competition among all participants. On the contrary, optimization models only represent one GenCo. Consequently, in the latter models, the market is synthesized in the representation of the price clearing process, which can be modeled as exogenous to the optimization program or as dependent of the quantity supplied by the GenCo of interest. The equilibrium models are more suitable to long-term planning and market power analysis since they consider all participants.

Simulation models are an alternative to equilibrium models when the problem under consideration is too complex to be addressed within a formal equilibrium framework. This thesis will focus on market analysis with equilibrium models.

A *Single-firm optimization models:*

The approaches based on the profit maximization problem of one firm (i.e. GenCo) are grouped together into the single-firm optimization category. These models take into account relevant operational constraints of the generation system owned by the firm of interest as well as the price clearing process. For example, the better computational tractability of optimization models enables them to deal with difficult and detailed problems, such as building daily bid curves in the short-term. For instance, Rajamaran *et al*. [10] describe and solve the self commitment problem of a generation firm in the presence of exogenous price uncertainty. A new framework to build bidding strategies for power suppliers in an electricity market is presented with imperfection of knowledge of rival suppliers in [11].

B *Equilibrium models:*

The oligopoly market equilibrium analysis has been widely used in recent years. In economics, market equilibrium refers to a condition where a market price is established through competition such that the amount of goods or services sought by buyers is equal to the amount of goods or services produced by sellers. This price is often called the equilibrium price or market clearing price and will tend not to change unless demand or supply change. There are several oligopoly equilibrium models available, the most prominent being the Cournot model, Bertrand model, Stackelberg model, Supply

Function Equilibrium (SFE) model and conjecture variables model. These models explicitly model the strategic behavior of suppliers. In these models, suppliers decide their bidding strategies and believe that rivals will not alter their strategies, and price is then determined solely by the strategies of the suppliers and the demand curve. Approaches which explicitly consider market equilibria are grouped together into the equilibrium models category. Although these approaches differ in regard to the strategic variables, they are based on the concept of Nash Equilibrium (NE)—the market reaches equilibrium when each firm's strategy is the best response to the strategies actually employed by its opponents.

1. Betrand model

The Betrand oligopoly model assumes that GenCos use the price as the strategy: each strategic GenCo decides its price to produce, while treating the output level of its competitors as a linear function of the price. The Bertrand model is used to predict the electricity prices in [12]. Bertrand model is based on the assumption that any GenCos can capture the entire market by pricing below other suppliers and supplying the entire demand. But generation capacity constraints and increasing marginal costs make this assumption invalid.

2. Stackelberg model

The Stackelberg model is a strategic game in economics in which the leader GenCo moves first and then the follower GenCos move sequentially. In game theory terms, the players of this game are leader(s) and follower(s). Stackelberg model for simulating deregulated electricity markets is introduced in [13] . The model is consisting of one or a few large producers and a larger number of fringe producers. It is assumed that the large producer(s) would adopt oligopoly strategy using their market power while the small producers would use Betrand-like strategy. The electricity is formulated by a Stackelberg model and a noninterior point algorithm is used to solve this Stackelberg equilibrium [14]. Numerical examples illustrate that the leader participant can abuse market power and increase in the presence of tighter transmission capacity constraints.

3. Cournot model

The Cournot oligopoly model assumes that strategic GenCos employ quantity strategies: each strategic GenCo decides its quantity to produce, while treating the output level of its competitors as a constant. The Cournot game is used to model electricity market in [15, 16] and the market models developed exploits the standard approach to interpreting market equilibrium as defining the first order conditions for a related optimization problem. The California electricity market is simulated by a Cournot market model [2]. Simulation results show that there is high market price in high demand periods. Genetic Algorithm (GA) with a new mutation operator is presented and applied to determine the Cournot Game electricity market in [17]. The equilibrium solution is formulated as a single objective GA and accurate and reliable numerical solutions can be obtained. A new approach to find NE in electricity markets is presented in [18]. It is based on the Nikaido–Isoda function and a relaxation algorithm. The method can be seen either as centralized optimization or as distributed optimization, where the generating companies solve their own profit maximization subproblems. The Cournot equilibrium in a transmission-constrained network is investigated in [19]. Simulation results show that pure strategy equilibrium can break down even when a transmission constraint exceeds the value of the unconstrained Cournot equilibrium line flow. The Cournot bidding electricity market with congestion management is modeled as a three level optimization problem in [20]. A statistical methodology is then proposed to solve this problem. A pay off matrix approach is proposed to solve the transmission constrained market equilibrium in [21, 22]. The proposed method obtains the mixed strategy NE that other iterated NE search method is difficult to obtain. The Cournot model can also be used to study the two-settlement electricity markets. Determination of the equilibrium in the markets is modeled as an Equilibrium Problem with Equilibrium Constraints (EPEC) by Cournot model, in which each GenCo solves a Mathematical Program with Equilibrium Constraints (MPEC) in [23]. Cournot model is well tractable and is widely used in market modeling. But it is difficult to handle a market with inelastic demand. However, the short-run demand elasticity in electricity markets is almost zero. As a result, price predictions from Cournot models depend on assumptions about a competitive fringe are not reliable.

4. SFE model

The general SFE model is introduced by Klemperer and Meyer [24]. The generators compete for the spot market by submitting their bids in the form of supply functions, which state the amount they would be willing to produce at any price. Several studies have used SFE models to consider the England and Wales market and other electricity markets. Green and Newbery [25] assume that each GenCo submits a smooth supply schedule, relating amount supplied to marginal price and look for the noncooperative

NE of the spot market, which implies a markup on marginal cost. Green [26] further models the effect of three policies that could increase the amount of competition in the electricity spot market in England and Wales. The linear supply function model with asymmetric GenCos is introduced in the analysis. He also analyzes the electricity contract market in England and Wales in [27]. He models competition in the spot market with supply functions and linear marginal costs. Rudkevich *et al*. [28] model a pool-based electricity market as a noncooperative game with a number of identical profit-maximizing GenCos. They use the analytical solution of SFE and relax the convexity and differentiability conditions to allow for the realistic step-wise supply curves to be studied. Rudkevich further presents a stylized model of the learning process through which GenCos can adjust their supply bidding strategies in order to achieve a rational profit-maximizing equilibrium behavior in the form of SFE [29]. Baldick and Hogan [30] consider a supply function model of an electricity market where strategic GenCos have capacity constraints. They show that if GenCos have heterogeneous cost functions and capacity constraints, then the differential equation approach to finding the equilibrium supply function may not be effective because it produces supply functions that fail to be nondecreasing. They analyze the nondecreasing constraints and characterize piece-wise continuously differentiable equilibrium. To find stable equilibria, they numerically solve for the equilibrium by iterating in the function space of allowable supply functions. Baldick *et al*. [31, 32] consider an SFE model of interaction in an electricity market, assuming a linear demand function and considering a competitive fringe and several strategic players with capacity limits and affine marginal costs. They assume that bid rules allow affine or piecewise affine nondecreasing supply function by GenCos and extend the results of Green and Rudkevich concerning the linear SFE solution. The capacity constraints are introduced, and an ad hoc approach to constructing piece-wise affine supply curves is proposed. A new uniform framework of electricity market analysis based on co-evolutionary computation is developed for SFE oligopoly electricity markets in [33]. The piece-wise SFE with nonconvex cost function that are difficult to be handled by the analytical approaches are also investigated.

Recently, some studies have been performed on determination of the SFE with transmission constraints. Baldick [34] investigates SFE in bid-based electricity markets with transmission constraints. He has demonstrated that the parameterization of the supply function model has a significant effect on the calculated results. The market equilibrium is modeled as a two-level optimization problem in which participants try to maximize their profit under the constraints, and their dispatch and price are determined by the Optimal Power Flow (OPF) in [35]. References [36, 37] formulate the problem of calculating SFE in the presence of transmission constraints as a MPEC.

According to these reviews, the SFE, which is originally developed as a way of modeling how competitors could achieve profit maximizing equilibria in the marketplace under conditions of uncertain demand [24], appears to be a promising model of interaction in deregulated power markets. Until now, short-run electricity demand elasticity appears to have been very low, again making the SFE method more applicable to electricity market modeling. SFE has been chosen as the basis for many power market models, at least for those markets where transmission network constraints could be ignored. SFE competes with the Cournot model as a practical tool for studying oligopoly in the electricity industry. SFE is attractive compared to Cournot because it offers a more realistic view of electricity markets, where bid rules may require suppliers to offer a price schedule that may apply throughout a day, rather than simply put forth a series of quantity bids over a day.

5. Equilibrium model with conjecture variable

The Conjectural Variation (CV) method can be used to simulate the strategic behavior of a game with imperfect information in actual electricity market. Another advantage of CV method is that it can easily model a market with different players: leaders, followers, or price takers. The approach of conjectural supply function is proposed by Garcia-Alcalde to simulate the Spain electricity market effectively in [38] and applied by Day and Hobbs in simulation of England and Wales market with linear Direct Current (DC) network [39]. Both papers [38, 39] only concentrate on the static equilibrium, but ignore the dynamic characteristics of CV, which is suitable to be applied in the learning process in the electricity market. A conjectural variation based learning method is proposed for GenCos to improve their strategic bidding performance in a spot electricity market taking account of the expected reaction of their rivals [40]. With the application of conjecture, each GenCo can make its optimal generation decision in the learning process according to available information published in the electricity market. Examples are used to illustrate that motivation is existed for each GenCo to start learning, and learning of all GenCos will decrease the market clearing price of electricity and improve the total social welfare. Conjecture Variable based Bidding Strategy (CVBS) method is used by GenCos to improve their strategic bidding and maximize their profits in real electricity spot markets with imperfect information [41]. A GenCo using CVBS integrates its rivals into one fictitious competitor and estimate its generation and reaction to the GenCo's change of output so that an optimal decision can be made accordingly. It is shown that classical Game Theoretic Bidding Strategies (GTBS) are special cases of CVBS families, and the system equilibrium reached via CVBS is NE. The analytic conclusions have been validated by computer simulations.

C Simulation models:

Simulation models are an alternative to equilibrium models when the problem under consideration is too complex to be addressed within a formal equilibrium framework. Simulation models typically represent each agent's strategic decision dynamics by a set of sequential rules that can range from scheduling generation units to constructing offer curves that include a reaction to previous offers submitted by competitors. The great advantage of a simulation approach lies in the flexibility it provides to implement almost any kind of strategic behavior. However, this freedom also requires that the assumptions embedded in the simulation be theoretically justified.

In many cases, simulation models are closely related to one of the families of equilibrium models. For example, when in a simulation model GenCos are assumed to take their decisions in the form of quantities, the authors will typically refer to the Cournot equilibrium model in order to support the adequacy of their approaches.

Otero-Novas *et al*. present a simulation model that considers the profit maximization objective of each GenCo while accounting for the technical constraints that affect thermal and hydro generating units [42]. Day and Bunn [43] propose a simulation model, which constructs optimal supply functions, to analyze the potential for market power in the England & Wales Pool. The modeling flexibility of simulation models allows for a wide range of purposes although there is still some controversy as to the appropriate uses of agent-based models. Bower and Bunn [44] present an agent-based simulation model in which GenCos are represented as autonomous adaptive agents that participate in a repetitive daily market and search for strategies that maximize their profit based on the results obtained in the previous session. The dynamics in two-settlement electricity markets is studied by an agent-based model in [45]. Numerical simulations imply that the access to the forward market leads to more competitive behaviors of the suppliers in the spot market, and thus to lower spot energy prices.

This section presents a comprehensive review of market power related issues in emerging electricity markets, with special emphasis on methods about equilibrium model for analysis of market power. Among these models, the Cournot and SFE models are the most extensively used models for analyzing pool-based electricity markets. Fortunately, direct estimation of the Cournot and SFE equilibria appears to be more feasible for electricity markets than the case for other commodities.

1.4 Market Analysis with Co-evolutionary Computation

Market equilibrium analysis is of fundamental importance because it provides the regulator with relevant information to identify and mitigate the exercise of market power [4]. It also provides GenCos with the appropriate information to maximize their respective profits, within the regulatory framework, by altering market clearing prices to their own respective benefits.

There are many methods, such as empirical analysis [19, 46, 47], agent-based simulation [45, 48-51], iterative NE search algorithms [23, 29, 35, 36, 52] and complementarity program method [37, 53, 54], employed to investigate the market equilibrium.

Although a lot of techniques have been employed to study the market equilibrium, no method has been extensively accepted, and the existing techniques need to be complementary each other. So an alternative tool should be developed to handle these problems. Recently, the application of co-evolutionary computation techniques to electricity market analysis has become a topical research area. Co-evolutionary computation approach has been successfully used to economical simulation and to determine the market equilibrium in complex games [33, 55, 56]. Reference [57] develops a co-evolutionary GA to model industrial organization games and has illustrated the potential of co-evolutionary computation in market simulation. Investigation on the dynamic behavior of market participants using a co-evolutionary approach has been performed in [58]. A hybrid co-evolutionary programming approach for NE search in games with local optima is proposed in [55] and the transmission-constrained electricity market is also studied. A new uniform framework of electricity market analysis based on co-evolutionary computation is developed for analyzing both Cournot [56] and SFE [33] electricity markets. The market players' repeated bidding behavior, nonlinear market models and piece-wise SFE with nonconvex cost function that are difficult to be handled by the analytical approaches are also investigated in [33, 56] by co-evolutionary computation approach. Simulation results have verified that the computation of co-evolutionary computation is highly efficient and is potentially practical.

This thesis will focus on several important issues as follows:

Firstly, when the transmission is considered, the profit function of market players may be nonconcave and discontinuous with many local optima. The conditions for the existence of the market equilibrium in a transmission-constrained power market are very complex. The thesis should reinvestigate the bidding behavior of market players in a constrained market with a powerful tool.

Secondly, the LSFE models with single parameter are investigated in [35-37, 46, 59], but the LSFE with multiple parameters should also be studied. When the capacity constraints are considered in the market analysis, determination of market equilibrium becomes a more challenging task.

Thirdly, when compared to actual markets, some of these works study single pricing period market equilibrium only and most of these works have not considered the inter-temporal constrains of the real market. It will be significative to model the effect of the actual GenCos on market-clearing prices in multi-period market setting with consideration of inter-temporal constraints.

Fourthly, due to the California electricity crisis, more and more researchers are convinced that forward market arrangement plays an important role as a means for market power mitigation in electricity markets [3]. Therefore, market equilibrium models are required to model the competition of generators in spot and contract markets. Then a new methodology need be developed to handle this challenging task.

Finally, co-evolutionary computation is a fast developing research area of evolutionary computation. In particular, co-evolutionary computation is of special importance in both its empirical evidence in market simulation and its underlying theoretical foundations because the dynamic behaviour of co-evolutionary computation is still unclear and need be studied.

This thesis establishes the mathematical models to study the above issues for electricity markets and uses co-evolutionary computation and game theories to analyze the equilibrium of electricity markets.

1.5 Thesis Layout

The organization of the thesis is as follows:

Chapter 1 presents the literature review on power market model and market power assessment and highlights the importance of the research in this thesis.

Chapter 2 provides an introduction to evolutionary computation and co-evolutionary computation. The general market model and market equilibrium are also introduced.

Determination of market equilibrium with a co-evolutionary computation algorithm is then preliminarily presented.

Chapter 3 further analyzes the performance of co-evolutionary computation in solving power market equilibrium problem with capacity constraints and transmission constraints. The effects of transmission and generation capacity constraints on the single pricing period NE in a day-ahead market is investigated. The LSFE and the Cournot market models are employed in the evaluation. The evaluation is based on a parallel Co-evolutionary Computation Algorithm (CCA). The existence or non-existence of the NE due to the above constraints are illustrated using a 2-bus test system and the IEEE 30-bus system. The effects of the different parameters settings of the LSFE model on the equilibria are also studied and compared with those found based on the Cournot model.

Chapter 4 is used to simulate the electricity market in a day-ahead pool-based market setting with co-evolutionary computation. It extends the co-evolutionary computation to analyze market power and bidding strategies in multi-period market with inter-temporal constraints. It reproduces actual market functioning to make the simulation results comparable to actual market settings. It is important to study the outcomes of markets in which the GenCos are compelled to bid consistent for multiple pricing period.

Chapter 5 presents a two-stage game model to formulate the competition of GenCos in bid-based pool spot markets and forward contract markets, as well as the interaction between these two markets. The issue of whether rational GenCos would voluntarily enter contract markets is examined and the factors which could affect the contractual behavior are studied. The effects of GenCos' cost parameters and demand elasticity on the bidding behavior of GenCos are studied. Two numerical examples are used to verify the theoretical results.

Chapter 6 summarizes the finding of the thesis and discusses some potential future works related to equilibrium analysis with the co-evolutionary computation.

1.6 List of Publications

Accepted Journal Papers:

S.X. Zhang, C.Y. Chung, K.P. Wong, H. Chen, "Analyzing Two-settlement Electricity Market Equilibrium by Coevolutionary Computation Approach," Accepted by IEEE transactions on power systems, 2009.

Referred Conference Papers:

S.X. Zhang, C.Y. Chung, K.P. Wong and H. Chen, "Determination of NE in Transmission-constrained Power market Using Nash Genetic Algorithm", International Conference on Electrical Engineering (ICEE) 2006, July, 2006, Korea.

Submitted Journal Papers:

S.X. Zhang, C.Y. Chung, K.P. Wong and H. Chen, "Equilibrium Analysis of Transmission and Generation Capacity Constrained Electricity Market Using Cooperative Coevolutionary Computation", submitted to Operations Research.

Journal Paper under Preparation:

S.X. Zhang, C.Y. Chung, K.P. Wong and H. Chen, "Multi-period Market Simulation: Using a Coevolutionary Computation Approach,"

CHAPTER 2 COEVOLUTIOANRY COMPUTATION

2.1 Introduction

Evolutionary Algorithms (EA) in the field of Evolutionary Computation (EC) have been widely applied in solving optimization problems, which are previously difficult or impossible to be solved. These algorithms include GA, Evolution Strategies (ES), Evolutionary Programming (EP) and Particle Swarm Optimization (PSO) etc. Recently, in order to solve extremely challenging problems, EAs have been combined among themselves and with knowledge elements of the problems, as well as with traditional approaches. EAs may offer many advantages such as shorter time for program development, strong solution searching capability for nonlinear and discrete problems, and robust performance with relatively insensitive to noisy and/or missing data.

This chapter will first provide an overview of EC and introduce the basic theory of EC and co-evolutionary computation; and then apply the co-evolutionary computation to determine the market equilibrium and analyze the power market.

2.2 Evolutionary Computation

There are a number of different classes of algorithms that make up the field of EC. They are notated as GA, EP, ES and Genetic Programming (GP). Although these four classes of EAs are different, they are all based on the same fundamental principles of Darwinian evolution. Another kind of evolution computation algorithms is swarm intelligence, such as Ant Colony Optimization (ACO) and PSO. EAs can be loosely recognized by the following criteria: iterative progress, growth or development; population based; guided random search; parallel processing; often biologically inspired. Finally a general framework of EA is given in Figure 2.1.

```
Procedure of EA
        t = 0;
        Initialize Pop(t);
        Evaluate Pop(t);
       While (End condition is not satisfied)
        {
          Parents(t) = Select_Parents(Pop(t));
          Offspring(t) = Procreate(Parents(t));
          Evaluate(Offspring(t));
          Pop(t+1)= Replace(Pop(t),Offspring(t));
          t = t + 1;
          }
```

Figure 2.1: Pseudo-code of EA

2.2.1 Genetic Algorithm

GA was formally introduced in the 1970s by John Holland at University of Michigan [60]. A GA is a search technique used in computing to find true or approximate solutions to optimization and search problems. GAs are a particular class of EAs that use techniques inspired by evolutionary biology such as inheritance, mutation, selection, and crossover (also called recombination) [60].

GAs are implemented as a computer simulation in which a population of abstract representations (i.e. chromosomes or genotype or genome) of candidate solutions (i.e. individuals or phenotypes) to an optimization problem evolves toward better solutions. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated. Multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly mutated) to form a new population. The new population is then used in the next iteration of the algorithm.

The flowchart of the classic GA is showed in Figure 2.2 and its procedure is described as follows:

1. [Starting] Generate random population of chromosomes (suitable solutions for the problem)
2. [Fitness evaluation] Evaluate the fitness of each chromosome in the population
3. [Creating new population] Create a new population by repeating following steps until the new population is complete

- [Selection] Select two parent chromosomes from a population according to their fitness (the better fitness, the bigger chance to be selected)
- [Crossover] With a crossover probability, cross over the parents to form new offspring (children). If no crossover is performed, the offspring is the exact copy of parents.
- [Mutation] With a mutation probability, mutate new offspring at each locus (position in chromosome).
- [Accepting] Place new offspring in the new population

4. [Replacing] Use new generated population for a further run of the algorithm
5. [Testing] If the termination condition is satisfied, stop, and return the best solution in the current population
6. [Looping] Go to step 2

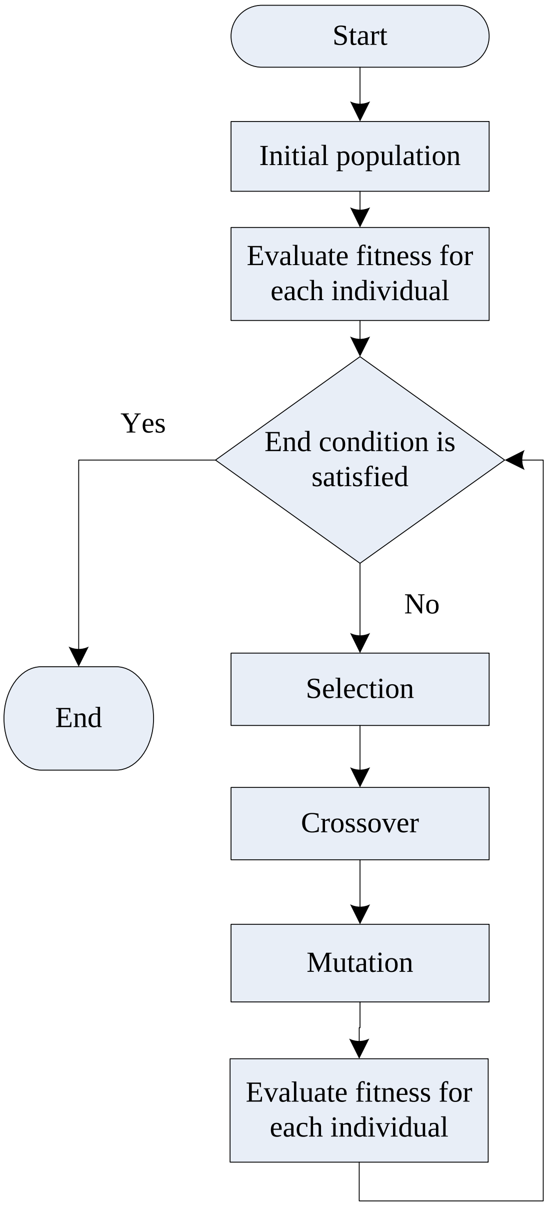

Figure 2.2: Flowchart of GA

2.2.2 Evolutionary Strategies and Evolutionary Programming

ES [61] employs real-coded variables and, in its original form, it relies on mutation as the search operator. It has evolved to share many features with GA. The major similarity between these two types of algorithms is that they both maintain populations of potential solutions and use a selection mechanism for choosing the best individuals from the population. The main differences are: GAs rely mainly on recombination to explore the search space, while ES uses mutation as the dominant operator; and ES is an abstraction of evolution at individual behavior level, stressing the behavioral link between an individual and its offspring, while GAs maintain the genetic link.

EP [62] is a stochastic optimization strategy similar to GA, which places emphasis on the behavioral linkage between parents and their offspring, rather than seeking to emulate specific genetic operators as observed in nature. EP is similar to ES, although the two approaches are developed independently. Like both ES and GAs, EP is a useful method of optimization when other techniques such as gradient descent or direct analytical discovery are not possible. Combinatorial and real-valued function optimization in which the optimization surface or fitness landscape is “rugged” are well suited for EP.

2.2.3 Particle Swarm Optimization

In 1995, Kennedy and Eberhart first introduced the PSO method, motivated by social behavior of organisms such as fish schooling and bird flocking [63]. PSO, as an optimization tool, provides a population-based search procedure in which individuals (i.e. particles) change their positions (i.e. states) with time. In a PSO system, particles fly around in a multidimensional search space. During flight, each particle adjusts its position according to its own experience, and the experience of neighboring particles, making use of the best position encountered by itself and its neighbors. The swarm direction of a particle is defined by the set of particles neighboring the particle and its history experience. PSO is an exciting new methodology in evolutionary computation. It is somewhat similar to a GA in that the system is initialized with a population of random solutions. Unlike other algorithms, each potential solution (i.e. a particle) is also assigned a randomized velocity and then flown through the problem hyperspace. PSO has been found to be extremely effective in solving a wide range of engineering problems. It is very simple to implement (the algorithm comprises two lines of computer code) and solve problems very quickly [64].

PSO is described as follows:

$$\begin{aligned} v_{i,j}^{(t+1)} &= wv_i^{(t)} + c_1 rand()(pbest_{i,j} - x_{i,j}^{(t)}) + c_2 rand()(gbest_j - x_{i,j}^{(t)}) \\ x_{i,j}^{(t+1)} &= x_{i,j}^{(t)} + v_{i,j}^{(t+1)} \end{aligned} \tag{2.1}$$

where

$i \in 1,...,N$	N is the number of population size
$j \in 1,...,d$	d is the number of dimension
$t \in 1,...,T$	T is the number of maximum generation
w	inertia weight factor
c_1, c_2	acceleration constant
$v_{i,j}^{(t)}$	uniform random value in the range [0,1]
$x_{i,j}^{(t)}$	velocity of particle at iteration
$pbest_{i,j}$	the best previous position of the i th particle
$gbest_j$	the value of $pbest_i$ with the lowest fitness

2.3 Co-evolutionary Computation

The simplest definition about a co-evolutionary algorithm is that “a co-evolutionary algorithm is an EA (or collection of EAs) in which the fitness of an individual depends on the relationship between that individual and other individuals” [65]. Such a definition immediately imbues these algorithms with a variety of views differing from those of standard EAs. For example, one might favor the view that individuals are not evaluated at all, but in fact their interactions are evaluated. Alternatively, one might look at individual fitness evaluation from the perspective of a dynamic landscape, given that the result of the evaluation is contextually dependent on the state of other individuals. In either case it is clear that they differ in profound ways from the traditional EAs.

2.3.1 Development of Co-evolutionary Computation

In fact, most works in co-evolutionary algorithms are in the area of competitive coevolution in the early time. The most popular competitive coevolution has been applied to game playing strategies [66]. Competition has played a vital part in attempts to coevolve complex agent behaviors [67] so coevoluiontary algorithm has also been applied to a variety of machine learning problems.

Potter and De Jong first propose cooperative evolutionary computation by developing a cooperative co-evolutionary algorithm for static function optimization through problem decomposition [68]. In this model, each population contains individuals representing a component of a larger solution. The populations evolve almost independently and interact only to obtain their fitness. Fitness of an individual representing a subcomponent is equal to the quality of the whole-problem solution obtained by assembling that individual with individuals representing the other subcomponents (for cooperative co-evolutionary computation, these individuals are usually called collaborators). Wiegand [69] attempts to make the algorithm more adaptively allocate resources by allowing migrations of individuals from one population to another. Since initial results of this method are promising, a framework for using cooperative co-evolutionary computation algorithms is developed in [70] and further extended in [65].

The main difference between cooperative and competitive co-evolutionary algorithms is the way that their individuals interact with each other. In the case of cooperative algorithms, individuals are rewarded when they work well with other individuals and punished when they perform poorly together. In the case of competitive algorithms, however, individuals are rewarded at the expense of those with which they interact. In this thesis, the Cooperative Co-evolutionary Algorithm (CCA) is employed.

CCA has promising applications in power system optimization and power market simulation. The decomposition and coordination methods based on the CCA are used in unit commitment [71] and reactive power optimization [72]. Another recent fast-developing area is the application of CCA [73] in determining the game equilibrium or analyzing the oligopolistic market [33, 55, 56]. CCA is found to be an effective and powerful approach for oligopolistic market analysis.

2.3.2 General Framework of Cooperative Co-evolutionary Computation

The basic framework of CCA is described in this section. It simulates the co-evolutionary mechanism in nature and adopts the notion of ecosystem. Multiple species coevolve and interact with each other and result in the evolution of the ecosystem. Each species evolves a bundle of individuals through the repeated application of a conventional EA. The individuals in the species are genetically isolated. But one species can interact with the others within a shared domain model.

Figure 2.3 shows the fitness evaluation phase of the EA from the perspective of species *i*. To evaluate an individual from species *i*, collaborators are formed with representatives from each of the other species. The domain model solves for the system variable. Then species *i* can use the system variable to evaluate the fitness of its individual. There are many possible methods for choosing representatives (i.e. collaborators). An obvious one is to simply let the current best individual from each species be the representative, and an alternative one is to randomly select an individual from each species to be the representative [65]. Here, the representative is the best individual in a species and is used as the collaborator.

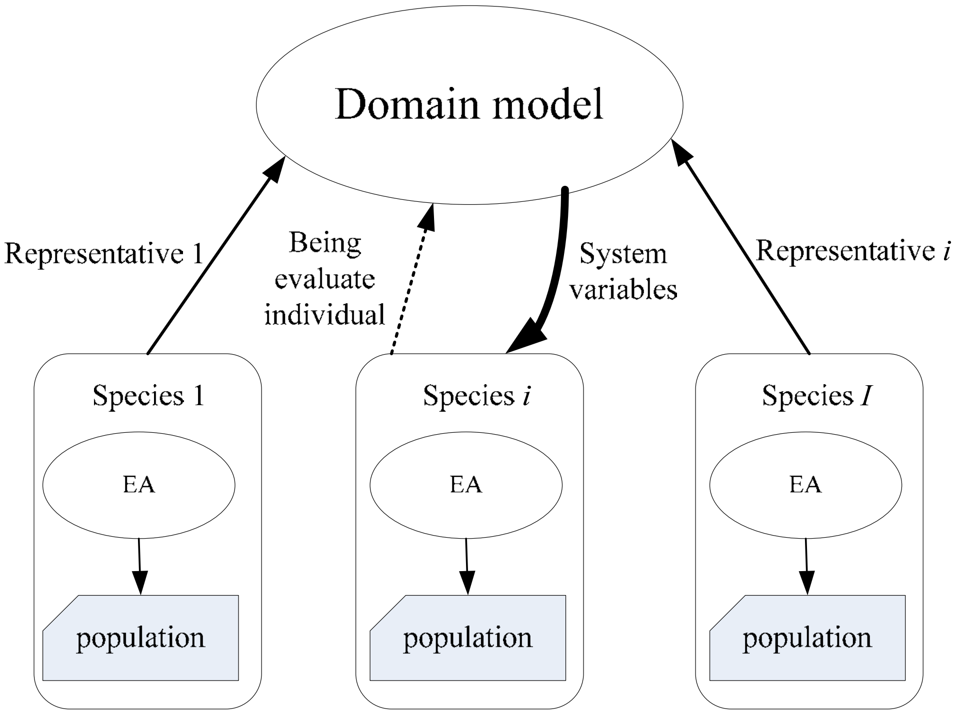

Figure 2.3: General framework of CCA

Wigand points out the many parameters that need to be set in CCA [65], such as which method of EA is used in each population and how the populations interact. CCA has a set of coevolution specific parameters whose values can greatly affect performance. It would be useful to have some knowledge of the effects of the reasonable values of parameters, in order to select a better one. In recent years, a lot of effort has been spent on generating such knowledge for CCA. Most studies [74-77] focus on collaboration schemes such as how many individuals should be used for evaluation, how these individuals should be selected, and how the outcomes of their interactions are aggregated. An initial study on the performance effects of population size and elitism is performed in [78] and then extended in [79]. But most of these studies [74-79] focus on using the decomposition technology to study a single objective optimization problem. The knowledge and methods of CCA parameters setting may not be suitable for the application of CCA in the game equilibrium determination. Indeed, this thesis has found that the CCA is observed to be more effective and efficient for market equilibrium determination when selection with elitism is used, the best individual is selected as representative, rather large mutation probability and population size are used.

A parameter called update timing which controls whether the CCA runs its species sequentially or in parallel [65] is introduced in this section. The term “sequential” refers to processing each population in a sequential order and choosing representatives from the current state of the other populations. Since the populations can change during each round, the order of the population selected for processing will affect the results. An alternate approach is the parallel one in which the individual populations are processed in parallel and synchronized only at the end of each round. In this approach, representatives are selected from the previous generation from each population. These two approaches are studied in [80] for pseudo-boolean functions and in [81] for functions defined on continuous real-number domains. Studies show the performance of the method is dependent on the problem property.

The pseudo-code of a CCA with parallel framework is given in Figure 2.4. The evolution of each species (i.e. population) is handled by an EA. A species means a population of EA in this algorithm and the species coevolves in parallel.

```
g = 0
for i=1:Num of Species
      initialize the species population  Pop_i^g in Species i
      evaluate fitness of each individual in  Pop_i^g
      choose a collaboration  Col_i^g  from  Pop_i^g
end
while g<max generations   do
   for i=1: Num of Species
         begin
            reproduction from  Pop_i^k  to get  Parent_i^g
            from  Parent_i^g  to get  Offspring_i^g (i.e. Pop_i^{g+1})
            evaluate fitness of each individual   in  Pop_i^{g+1}
   end
   for i=1: Num of Species
         choose a collaboration  Col_i^{g+1}  from  Pop_i^{g+1}
   end
     g = g + 1
end
```

Figure 2.4: Pseudo-code of parallel CCA

In CCA, species can calculate their best strategy based on information about what other species have done in the last generation [79]. Individuals in the species with higher fitness are at a productive advantage compared to individuals with lower fitness; hence the latter decreases in frequency in the new population (natural selection). In this situation species are viewed as being coded with a strategy and selection pressure favors species that are fitter whose strategy yields a higher payoff against the population.

Species adopt actions that optimize their expected payoff given what they expect others to do.

Since CCA explicitly models the reciprocity among the coevolving species, it embodies a dynamic process of strategy choice and interaction, which coincides with the framework of game theory. Recently, game theory, especially evolutionary game theory has begun to be used to analyze the dynamic behaviors of co-evolutionary approach [75]. Co-evolutionary computation is a new area in the research of evolutionary computation. Its theory and applications are still rapidly developing [79-83].

2.4 Determination of Power Market Equilibrium Using CCA

In a non-cooperative game, each player optimizes its own profit given that all the strategies of other players are fixed. The game will reach the NE when no player can further improve its profit by changing its strategy unilaterally [84]. For an *I*-player game, each player has its strategy set X_i and its payoff function is $\pi_i(x_1,..., x_i,..., x_I)$ where the strategy $x_i \in X_i$ and $i = 1,..., I$. Each player can only choose one strategy from its strategy set. If the strategy profile $(x_1,...,x_i,..,x_I)$ is the NE, it must satisfy the following equation:

$$\pi_i(x_1,..., x_i^*,..., x_N) \le \pi_i(x_1,..., x_i,.., x_N) \tag{2.2}$$

where $x_i^* \in X_i$.

2.4.1 General Framework of Electricity Pool Market

A general game equilibrium model of Bid-Based Pool (BBP) electricity market is introduced in this section. The market is modeled by a noncooperative game model, such as Cournot and LSFE models. It is assumed that *I* market players try to maximize their profit functions $f_i(x_1, x_2, ..., x_I)$ where the decision variables $x_i \in X_i$ in the market. X_i is the decision variable spaces (strategy set) of Player *i*. Each player submits its optimal trading strategy to the Independent System Operator (ISO) or Market Operator (MO). The trading strategy is different for different market models. Here for the standard Cournot model with quantity decision participants, the trading strategy is the quantity to be generated. ISO then calculates the market price according to the demand characteristics and market rules. ISO uses the market players' bidding strategies to determine the market signal (i.e. market price and players' transactions). Each player can calculate its profit with the market price and its trading strategy.

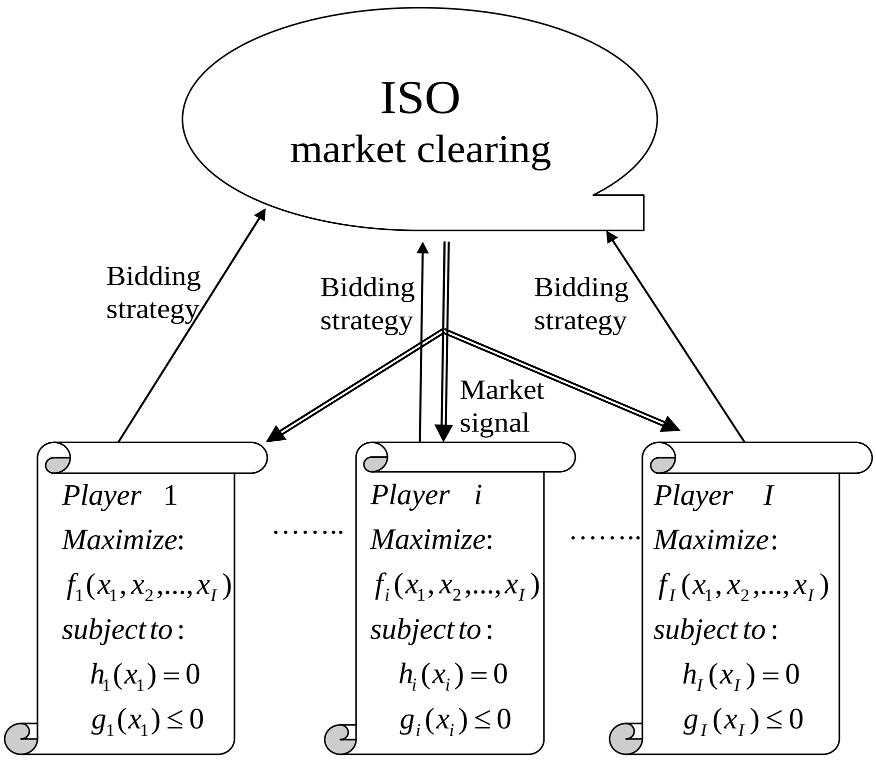

Figure 2.5: Electricity market modeling by equilibrium model

2.4.2 Determination of Market Equilibrium Using CCA

Many methods, such as empirical analysis [19, 46, 47], agent-based simulation [45, 48-51], iterative NE search algorithms [23, 29, 35, 36, 52] and complementarity program method [37, 53, 54], have been employed to determine the market equilibrium. Besides, some heuristic methods , such as learning and coordination between different players [85, 86], have been used to study the economic game.

Empirical analyses on market equilibrium are performed in [19, 46, 47]. The equilibrium is obtained by drawing the best response curves of the players, but this methodology is limited to small test systems.

Iterative NE search algorithms that use repeated individual profit maximization are employed to determine the NE in [23, 29, 35, 36]. Rudkevich [29] presents a model of the learning process in which each GenCo starts from the perfectly competitive supply function and adjusts the slope of supply function through a stylized formula and using the market observed data. Rudkevich proves that GenCos can achieve an SFE through this learning process. Iterative NE search algorithms have been applied to more complex games in [35, 36]. Hobbs *et al.* formulate the maximization problem of individual profits for each GenCo in a transmission constrained electricity market as a MPEC [36], and apply a penalty interior point algorithm to solve the problem. Weber and Overbye formulate the problem to determine the market equilibrium in the power market as a two-level optimization problem [35]. A modified Newton step is merged into the algorithm to optimize the individual profit. The iterative NE search algorithms that use repeated individual profit maximization are hard to handle a complex market because they often use local search methods [35, 36] with limited search step to solve the market players' profit maximization problems.

Another way to determine the market equilibrium is using the Linear Complementary Program(LCP) [53] or Nonlinear Complementary Program (NLP) [37]. Stoft applies LCP to a two-player game in an electricity market [53]. Although the algorithms have been well proven mathematically, they are limited to the bimatrix game. Wang *et al* determine the electricity market equilibrium with transmission constraints using the NLP method [37]. But the studies in [37] have not shown how to handle the situation when the market has no pure equilibrium or has an equilibrium continuum. In addition, the solution obtained by the NLP method may not be a pure NE when the optimization problem is not generalized convex nor are its constraints [87].

It is difficult to determine the NE in a complex game; and even impossible if the payoff functions are non-differentiable functions. So the CCA has been recently used as an alternative tool to determine the NE in power market [33, 55, 56].

In the CCA, each player is represented by a species. Each player will optimize its own benefit function and determine the best solution of its decision variable using an EA by fixing the decision variable of other players. To evaluate individuals from one species, collaborators (i.e. the representatives of each species) from each of the other species are needed. The last generation best decision variable of each player for parallel CCA or current best decision variable of each player for sequential CCA will be selected as the representative and sent to another player for next generation. The process will stop when the maximum number of generation is reached. In a multiple players' game, when the CCA converges to a solution at generation *k*, each player will not change its best variable because it could not find a better solution without changing the decision variable of another player. This means the fitness of species *i*'s individual in generation $l(l > k)$ is no larger than the best fitness of species *i* in generation *k*.

$$fitness_i(x_{1best}^k, ..., x_i^l, ..., x_{Ibest}^k) \leq fitness_i(x_{1best}^k, ..., x_{ibest}^k, ..., x_{Ibest}^k) \tag{2.3}$$

where $fitness_i(x_1, ..., x_i, ..., x_I)$ is the fitness function for species *i*, i.e. its payoff function. By comparing (2.2) and (2.3), if species *i* uses the player *i*'s payoff function $\pi_i(x)$ as the fitness function, (2.3) is satisfying the definition of the NE.

GA is found be more suitable for economic learning in [88]. It is shown that economic learning via GAs can be described as a specific form of an evolutionary game. The performances of different EAs, such as GA, EP and PSO, in simulating players' behaviors are compared [89]. The authors have pointed out that EP and PSO can be more appropriate than GA if solution space is well defined and both of them can utilize the previous global information. On the other hand, if the solution space is highly skewed and tortuous, the previous global information may be wrong and mislead the searching procedure in PSO and EP. Thus, GA will outweigh EP and PS in the later case. In a market game, the relationship and interaction of the market players are very complex. The dynamic behavior of one player is affected by strategies of other market players. The fitness landscape of a player's payoff function is usually unpredictable. Thus, GAs will be used to simulate bidding behaviors of GenCos in the CCA in this thesis.

CHAPTER 3 DETERMINATION AND ANALYSIS OF ELECTICITY MARKET EQUILIBIUM WITH TRANSIMISSION AND CAPACITY CONSTRAINTS

3.1 Introduction

Different equilibrium models have been used for the electricity market analysis including Cournot, Betrand, Stackelberg, SFE and Collusion models [4, 13, 90]. SFE and Cournot models are extensively used in market power analysis. There are many successful application cases to simulate the power market using the SFE models [25, 26, 29, 30, 91] and Cournot models [56, 90]. However, most of these studies neglect the effect of the transmission constraints.

Recently, some studies [19, 35-37, 46, 47, 53-55, 59, 87, 92-94] have been performed on determination of the market equilibrium with transmission constraints. A two-level optimization model is used in which participants try to maximize their profits under the transmission constraints, and their power dispatch and price are determined by the OPF.

When the transmission is considered, the profit function of market players may be nonconvex and discontinuous with many local optima. The conditions for the existence of the market equilibrium are very complex. The following three possible situations exist:

1. One pure NE exists when the transmission constraints are not so tight.
2. No pure NE exists due to the transmission congestion [19, 46, 47].

3. A NE continuum in LSFE market models appears due to transmission congestion [35, 46, 47].

The LSFE models with single supply function parameter are investigated in [35-37, 46, 59], but the LSFE with multiple supply function parameters should also be studied. When the generation capacity constraints are considered in the market analysis, determination of market equilibrium becomes a more challenging task. A new global search method needs to be explored for market analysis and equilibrium determination in more realistic and complicated conditions.

In this chapter, electricity markets with transmission and generation capacity constraints are studied. A parallel Co-evolutionary Genetic Algorithm (CGA) is applied to determine the market equilibrium with transmission and generation capacity constrains. The performance of the parallel CGA is tested and the effects of the transmission constraints and generation capacity constraints on the behavior of market players and on the existence of the NE are investigated.

3.2 Model Formulation

Suppose there are I generators, J demands and N buses in the power system. The I generators belong to F GenCos. Generator i belonging to GenCo f is represented by $i \in S_f$. Each generator is assumed to have a strictly concave quadratic cost function:

$$C_i\left(P_{Gin}\right) = \frac{1}{2} a_i P_{Gin}^{\;2} + b_i P_{Gin} + c_i \quad i = 1, \ldots, I \tag{3.1}$$

where P_{Gin} is the quantity generated by Generator *i* at bus *n*; a_i, b_i and c_i are the coefficients of the Generator *i*'s cost function; $C_i(P_{Gin})$ is the cost of generator i . Therefore the marginal cost function is affine for each generator as follows:

$$\frac{dC_i}{dP_{G\,in}}\left(P_{G\,in}\right) = a_i P_{G\,in} + b_i \quad i = 1, \ldots, I \tag{3.2}$$

Assume that each demand has an inverse linear demand function:

$$p_n(P_{Djn}) = -d_j P_{Djn} + e_j \qquad j = 1, ..., J \tag{3.3}$$

where p_n and P_{Djn} are the price and the quantity of demand *j* at bus *n* respectively; d_j and e_j are the coefficients of the demand function with $d_j \geq 0, e_j \geq 0$. Therefore the demand benefit function can be represented by:

$$B_j(P_{Djn}) = -\frac{1}{2} d_j P_{Djn}^2 + e_j P_{Djn} \qquad j = 1, ..., J \tag{3.4}$$

where $B_j(P_{Djn})$ is the cost of demand *j*.

If the transmission loss is assumed to be negligible, the aggregate demand will be equal to the total output of all the generators in the market as shown below:

$$\sum_{i=1}^{I} P_{G\,in} = \sum_{J=1}^{J} P_{Djn} \tag{3.5}$$

3.2.1 Market Model

LSFE model and the less competitive market model, Cournot model, are described in this section.

1) LSFE Model

In the day-ahead power market, the generators are assumed to submit a bid to ISO, in the form of Linear Supply Function (LSF) in each pricing period (i.e. one hour). Each LSF includes an intercept and a slope as follows:

$$p_n\left(P_{Gin}\right) = \alpha_i P_{Gin} + \beta_i \quad i = 1, \ldots, I \tag{3.6}$$

where α_i and β_i are the bidding strategies of the Generator *i*.

Baldick summarizes the parametrization of supply function into four categories [34]. The notations are different from [34].

1. *a*-parametrization, where Generator *i* can choose α_i in (3.6) arbitrarily but is required to specify a fixed and pre-chosen value of β_i . In this chapter, $\beta_i = b_i$ is selected.
2. *b*-parametrization, where Generator *i* can choose β_i in (3.6) arbitrarily but is required to specify a fixed and pre-chosen value of α_i. In this chapter, $\alpha_i = a_i$ is selected.
3. $(a \propto b)$ -parametrization, where Generator *i* can choose α_i and β_i subject to the condition that α_i and β_i have a fixed linear relationship. The LSF described in (3.7) is studied in this chapter, where k_{Gi} is the bidding variable:

$$p_n\left(P_{Gin}\right) = k_{Gi}(a_i P_{Gin} + b_i) \quad i = 1, \ldots, I \tag{3.7}$$

4. (a, b) -parametrization, where Generator *i* can choose α_i and β_i arbitrarily.

Then each GenCo will maximize its own profit where the decision variables are α_i and β_i. The optimization problem can be formulated as:

$$\begin{aligned} Max \quad & \pi_f(\alpha_1, \beta_1, ..., \alpha_i, \beta_i, ..., \alpha_I, \beta_I) \\ & = \sum_{i \in S_f} (p_n P_{Gin} - C_i(P_{Gin})) \qquad f = 1, ..., F \end{aligned} \tag{3.8}$$

where p_n, the nodal price at bus *n*, is determined by ISO.

Once each generator given its bidding, the ISO needs to solve the DC OPF problem in (3.9) for determining the corresponding generating output of each generator (P_{Gin}), the load demand of each demand (P_{Djn}) and the nodal price (p_n). The objective of this market clearing problem is to maximize a quasi-social welfare (defined by the benefit of demands minus the submitted costs of the generators), subject to power balance constraint, transmission constraints and generation capacity constraints.

$$
\begin{aligned}
Max \quad \Gamma_{ISO} &= \sum_{j=1}^{J} B_j(P_{Djn}) - \sum_{i=1}^{I} C_i\left(P_{Gin}\right) \\
&= \sum_{j=1}^{J} \left(-\frac{1}{2} d_j P_{Djn}{}^2 + e_j P_{Djn}\right) \\
&\quad - \sum_{i=1}^{I} \left(\frac{1}{2} \alpha_i P_{Gin}{}^2 + \beta_i P_{Gin}\right) \\
\text{s.}t. \quad & \mathbf{H}^T(\mathbf{P_G} - \mathbf{P_D}) = 0 \quad \text{Power balance constraint} \\
& \mathbf{T}(\mathbf{P_G} - \mathbf{P_D}) \le \overline{\mathbf{F}} \quad \text{Transmission constraints} \\
& \underline{\mathbf{P_G}} \le \mathbf{P_G} \le \overline{\mathbf{P_G}} \quad \text{Capacity constraints of generators} \\
& \underline{\mathbf{P_D}} \le \mathbf{P_D} \le \overline{\mathbf{P_D}} \quad \text{Capacity constraints of demands}
\end{aligned}
\tag{3.9}
$$

where matrix **T** is the sensitivity of the branch flows to nodal net injections, i.e. shift factors; **H** is a properly dimensioned vector with all ones.

The Lagrangian function for this ISO optimization problem is:

$$
\begin{aligned}
\max \quad & \Gamma_{ISO} = \sum_{j=1}^{J} B_j(P_{Djn}) - \sum_{i=1}^{I} C_i\left(P_{Gin}\right) + \lambda \mathbf{H}^T(\mathbf{P_G} - \mathbf{P_D}) \\
& + \boldsymbol{\mu}^T(\mathbf{T}(\mathbf{P_G} - \mathbf{P_D}) - \overline{\mathbf{F}}) + \hat{\boldsymbol{\tau}}^T(\mathbf{P_G} - \overline{\mathbf{P_G}}) \\
& + \breve{\boldsymbol{\tau}}^T(\underline{\mathbf{P_G}} - \mathbf{P_G}) + \hat{\boldsymbol{\upsilon}}^T(\mathbf{P_D} - \overline{\mathbf{P_D}}) + \breve{\boldsymbol{\upsilon}}^T(\underline{\mathbf{P_D}} - \mathbf{P_D})
\end{aligned}
\tag{3.10}
$$

where λ is the Lagrangian multiplier of power balance constraint; $\boldsymbol{\mu}, \hat{\boldsymbol{\tau}}, \breve{\boldsymbol{\tau}}, \hat{\boldsymbol{\upsilon}}, \breve{\boldsymbol{\upsilon}}$ are the corresponding Lagrangian multipliers vector associated with transmission constraints, generators' upper and lower generation capacity limits as well as demands' upper and lower demand capacity limits respectively.

The nodal price can be obtained as follows:

$$p_n = \lambda + \sum_{m=1}^{M} \mu_m T_{mn} \qquad n = 1,\ldots,N \tag{3.11}$$

where T_{mn} is the element (m, n) of matrix $\mathbf{T}$; and M is the number of transmission lines.

2) Cournot Model

In Cournot model, the generators are assumed to use their quantities as bidding variables. The optimization problem of GenCo f is described in (3.12) where the decision variables are P_{Gin} ($i \in S_f$).

$$\begin{aligned} Max \quad & \pi_f (P_{G1n},\ldots,P_{Gin},\ldots,P_{GIn}) \\ & = \sum_{i \in S_f} \left(p_n P_{Gin} - C_i(P_{Gin}) \right) \qquad f = 1,\ldots,F \end{aligned} \tag{3.12}$$

Since P_{Gin} of generators are known, ISO can determine the corresponding P_{Djn} and p_n similar to the optimization problem in (3.10) of the LSFE model, but with the following equation:

$$\begin{aligned} & Max \quad \Gamma_{ISO} = \sum_{j=1}^{J} B_j(P_{Djn}) + \lambda \mathbf{H}^T (\mathbf{P_G} - \mathbf{P_D}) \\ & + \boldsymbol{\mu}^T (\mathbf{T}(\mathbf{P_G} - \mathbf{P_D}) - \overline{\mathbf{F}}) + \widehat{\boldsymbol{\tau}}^T (\mathbf{P_G} - \overline{\mathbf{P_G}}) \\ & + \breve{\boldsymbol{\tau}}^T (\underline{\mathbf{P_G}} - \mathbf{P_G}) + \widehat{\boldsymbol{\upsilon}}^T (\mathbf{P_D} - \overline{\mathbf{P_D}}) + \breve{\boldsymbol{\upsilon}}^T (\underline{\mathbf{P_D}} - \mathbf{P_D}) \end{aligned} \tag{3.13}$$

3.2.2 Determination of Market Equilibrium Using CGA

Equilibrium determination of an electricity market with F GenCos (market players) can be considered as a two-level optimization problem, in which the first level is the ISO's market clearing optimization problem in (3.10) for LSFE model or (3.13) for Cournot model used to determine the market signal including p_n, P_{Gin} and P_{Djn}; and the second level is the maximization of GenCos' benefits in (3.8) for LSFE model or

(3.12) for Cournot model used to optimize the corresponding bidding variables of each GenCo [35].

CCA is applied to solve this problem. Each GenCo is represented by a species, which coevolves using the standard GA operators including crossover and mutation [60].

The procedures can be summarized as follows:

Step 1: Set the basic parameters of CGA including maximum generation number, population size of each species, crossover rate and mutation rate.

Step 2: The individual of each species, which includes the bidding variable of the GenCos, is initialized. All the initial representatives of each species are set randomly.

Step 3: The standard GA is applied to solve the optimization problem of each GenCo in (3.8) or (3.12). For each individual in the species, the ISO market clearing problem in (3.7) is first solved by the quadratic programming technique to determine the corresponding p_n and P_{Gin} for the generator or P_{Djn} for the demand; and then this individual is assigned a fitness value according to the profit function in (3.8) or (3.12). The number of generation for the standard GA is set to be the number of decision variables in species *i*.

Step 4: The best individual of each species (i.e. individual with the highest fitness value) is selected as the representative and sent to other GenCos.

Step 5: Repeat Steps 3-4 using the updated collaborators and also keeping the best strategy of each GenCo in the population (i.e. elitism) until the maximum generation number is reached.

3.3 Case Studies

In this section, the proposed method is applied to a 2-bus test system and the IEEE 30-bus test system. Results for perfect competition are also presented in both examples for the purpose of comparison with the LSFE results. The CGA parameters are given in Table 3.1.

Table 3.1: Parameters of CGA

Parameters	Description
Variable code	20 bit binary code
Initial population	Randomly initialized population
Population size	60
Maximum generation	200
Mutation	Bit-flip mutation (mutation probability= 0.1)
Crossover	Two-point crossover (crossover probability= 0.9)
Selection	Roulette selection and 5% population is elitism

3.3.1 2-Bus Test System

The test system with two generators and one demand is shown in Figure 3.1. The coefficients of generator's cost and demand functions are given in Table 3.2 [35]. The two generators belong to two GenCos respectively.

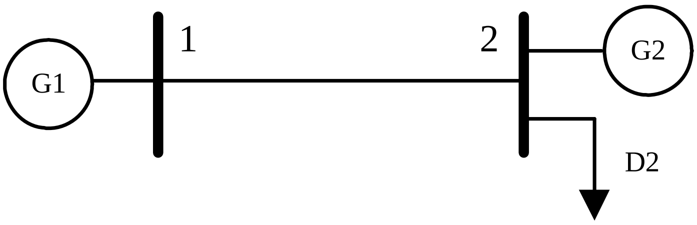

Figure 3.1: 2-bus test system

The LSFE under $(a \propto b)$-parametrization is used to illustrate the convergence process of the proposed algorithm in the 2-bus electricity market with transmission constraints and generation capacity constraints. The demand constraints is set as $\underline{P_{D2}}$ =0MW and $\overline{P_{D2}} = e_i / d_i$ =375MW. The upper and lower limits of k_{Gi} are assumed to be 20 and 0 respectively.

Table 3.2: Coefficients of demand function and generators' cost function

Bus number	Coefficient	1	2
Demand function	d_j(\$/(MW)^{2}h)	0	0.08
	e_j (\$/MWh)	0	30
Generators' cost function	a_i (\$/(MW)^{2}h)	0.02	0.02
	b_i (\$/MWh)	10	10
	c_i (\$/h)	0	0

A Effect of Transmission Constraints:

When the transmission limit ($\overline{F}$) is set to 180MW, which is a relatively large value, the best response curves are determined to identify whether there is a pure NE. For example, given a k_{G1} in each step, k_{G2} is varied within its decision range to find the corresponding value that gives the maximum profit of Generator 2. Repeating the above calculation step by step yields the best response curve of Generator 2. Similarly, the best response curve of Generator 1 can be obtained. The best response curves of both generators are shown in Figure 3.2. The intersection of the best response curves is the pure NE [84]. In this case, a unique NE is obtained and the proposed algorithm converges to the NE rapidly as shown in Figure 3.3.

When the transmission line becomes tight and $\overline{F}$ is reduced to 80MW, no pure NE exists because there is no intersection point of the best response curves as shown in

Figure 3.4. In Figure 3.5, it is also observed that the CGA will not converge to any solution.

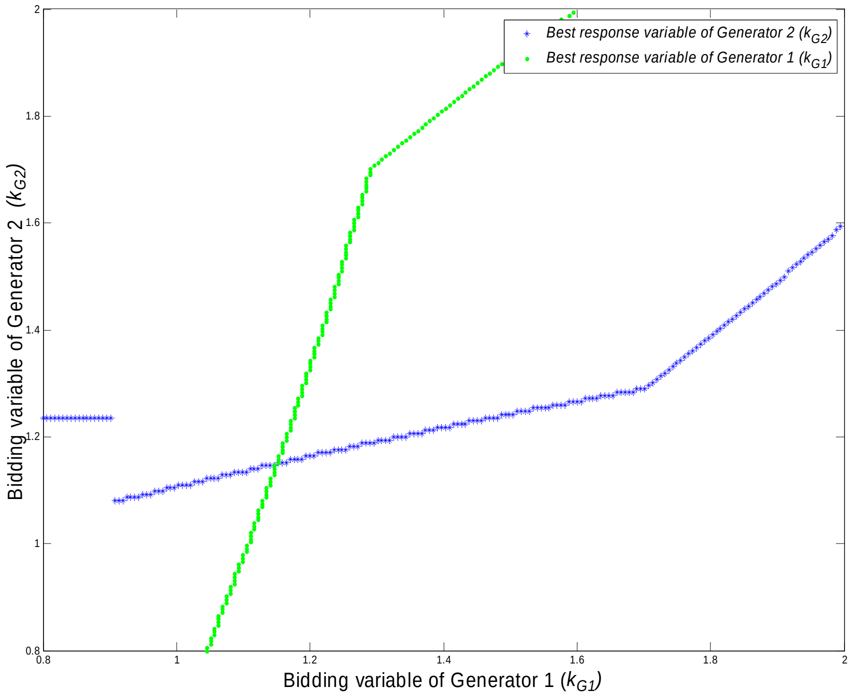

Figure 3.2: Best response curves for $\overline{F}$ = 180MW

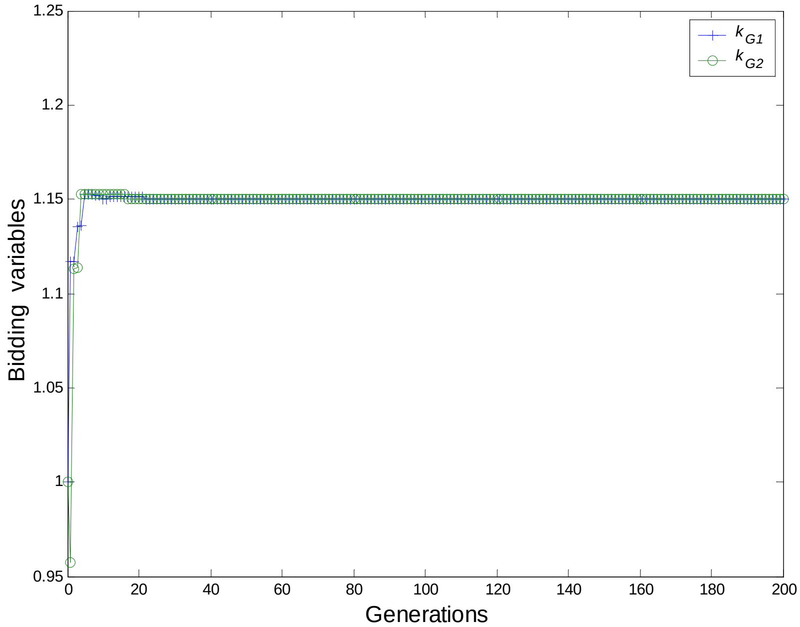

Figure 3.3: Evolution process of bidding variables for $\overline{F}$ =180MW

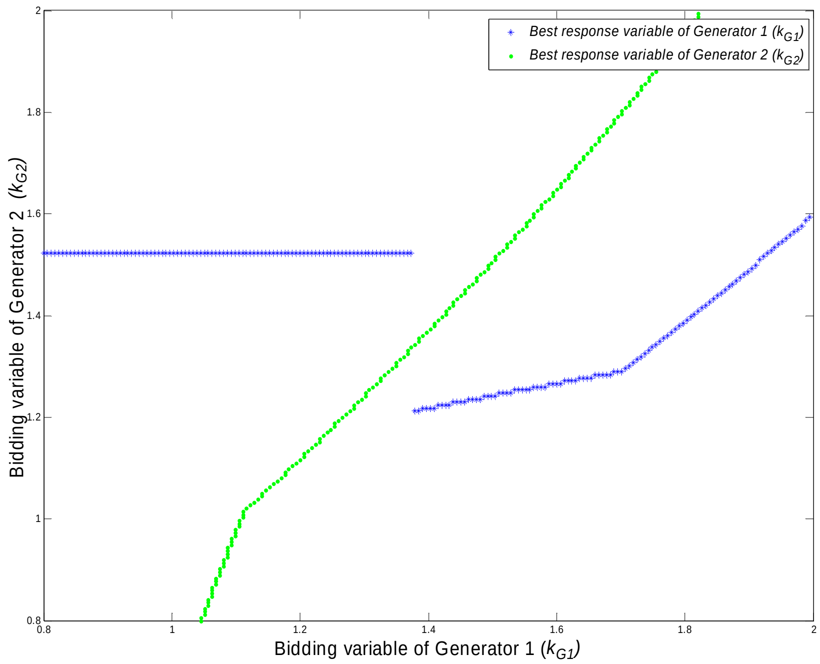

Figure 3.4: Best response curves for $\overline{F}$ = 80MW

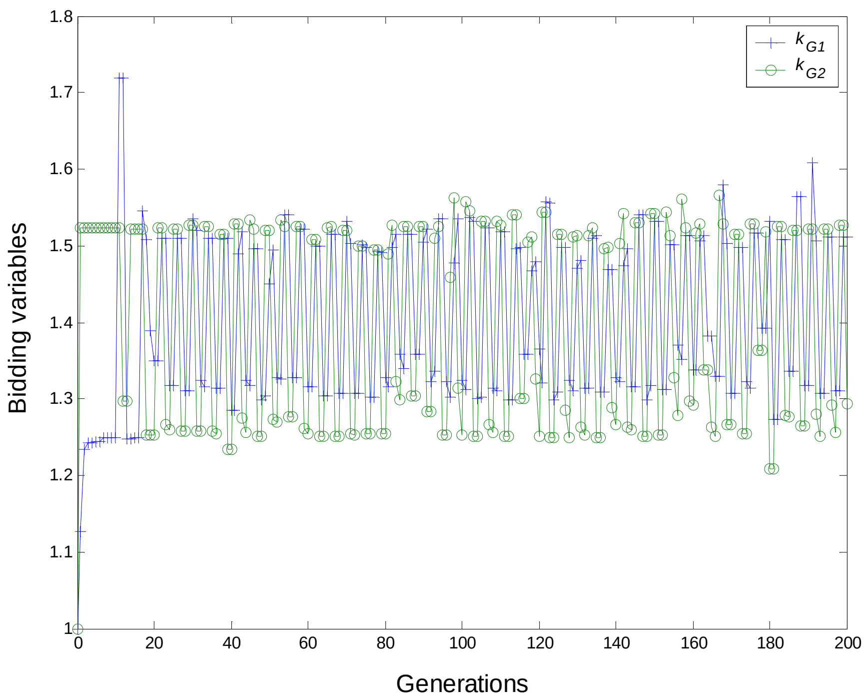

Figure 3.5: Evolution process of bidding variables for $\overline{F}$ =80MW.

In order to show the convergence process of CGA, the 2-bus test system is studied again by CGA with a large population size. All other CGA parameters in Table 3.1 are unchanged, except for the population size changed to 1000 which is a considerable large number. In each generation, each species will have a large probability to find its best response variable because the species population is very large. In Figures 3.6 and 3.7, the evolution direction of each species in each generation is to the generator's best response variable curve in which the generator will have the maximum profit. For example, the best variable set of the generators is $k^0 = (k^0_{1best}, k^0_{2best}) = (1, 1)$ in generation 0. Generator 1 will be attracted to k^1_{1best} in order to get higher profit. At the same time, Generator 2 will be attracted to k^1_{2best}. Then, after a generation the algorithm will evolve to $k^1 = (k^1_{1best}, k^1_{2best})$. After several generations, the algorithm can converge to the pure NE, i.e. the intersection of the best response curves as shown in Figure 3.6. No generator can find a better variable to alternate the variable selected previously so the generators have no incentive to change their variables.

When the transmission constraint is tighter, the limit cycle phenomenon presented by Weber [35] is observed in Figure 3.7. For example, at generation 2, the best solution of CGA evolves to k^2 and at generation 3, it is attracted to k^3 because Generator 2 has the highest profit in k^3. It then evolves to k^4 at generation 4 and k^5 at generation 5. Finally, it evolves and returns to k^2 at generation 6.

CGA is a global search algorithm and can avoid converging to a local optimal point as illustrated by the simulation results.

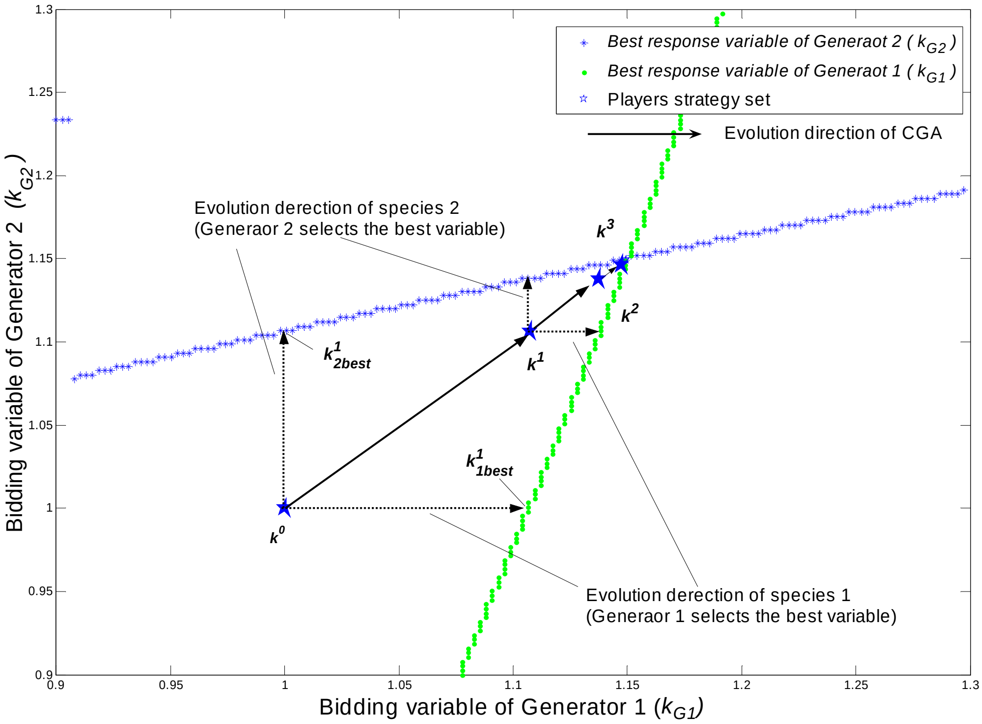

Figure 3.6: Convergence process for $\overline{F}$ =180MW

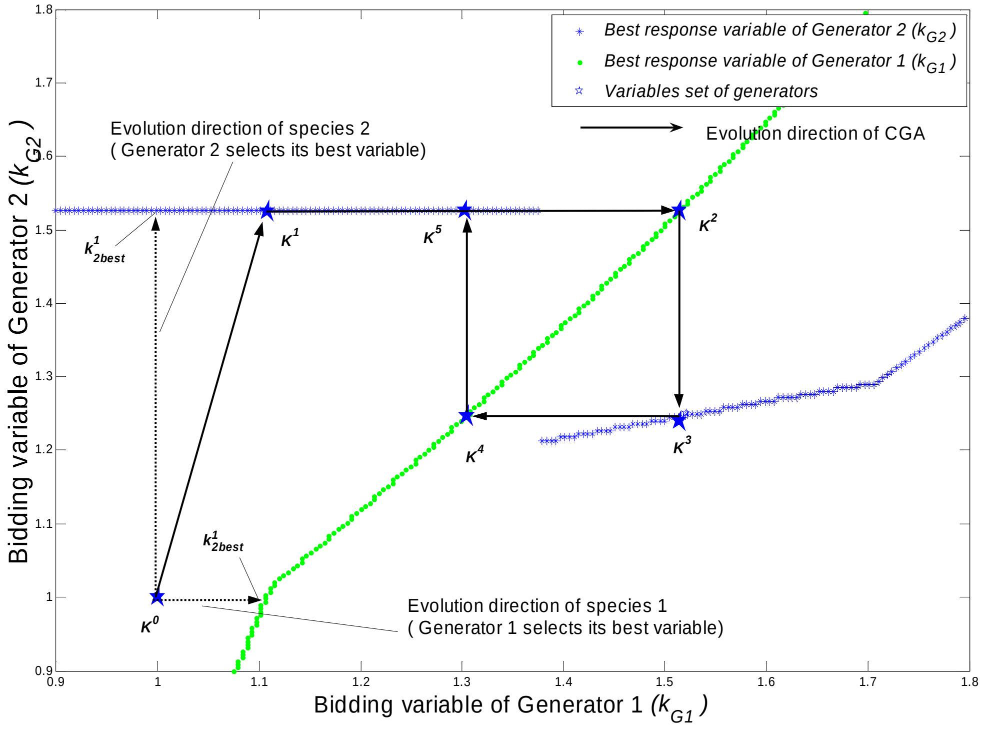

Figure 3.7: Convergence process for $\overline{F}$ =80MW

B Effect of Generation Capacity Constraints:

When the generator hits its generation capacity constraints, it cannot use its bidding variable to change its output to get more profit. The bidding variables' threshold can be determined by:

$$k_{Gi\,Lim} = \lambda /(a_i P_{G\,iLim} + b_i) \quad i = 1,\ldots, N \tag{3.14}$$

where $k_{Gi\,Lim}$ is equal to $k_{Gi\min}$ or $k_{Gi\max}$ when P_{GiLim} is equal to $\underline{P_{Gi}}$ or $\overline{P_{Gi}}$ respectively. On the one hand, if the output of a generator reaches its lower capacity limit ($\underline{P_{Gi}}$), the generator can select its bidding variable not less than the threshold ($k_{Gi\min}$) when other generators do not change their strategies. On the other hand, if its output reaches the upper limit ($\overline{P_{Gi}}$), it can select the bidding variable not larger than the threshold ($k_{Gi\max}$) when other generators do not change their strategies. An equilibrium continuum may exist in such situation.

Figure 3.8 shows there exists a NE continuum because the best response curve of Generator 1 has much intersection with response curve of Generator 2 when the market constraints are $\overline{F}$ =180 and $\overline{P_{G2}}$ =50MW. Generator 2 hits its upper capacity constraint and can select the bidding variable arbitrarily and no larger than $k_{G2\max}$=1.70 (Point A in Figure 3.8) if Generator 1 does not change its strategy k_{G1}=1.60. But if Generator 2 selects k_{G2} between 1.56 and 1.70 as its bidding strategy, Generator 1 will not satisfy its benefit and changes its strategy. For example, if k_{G2}=1.70, k_{G1} will become 1.30 (Point B in Figure 3.8). The equilibrium continuum is k_{G1}=1.60 and $k_{G2} \in$[0, 1.56] as shown in Figure 3.8. The NE continuum upper bound $k_{G2\max}^{(c)}$ of k_{G2} is smaller than $k_{Gi\max}$. Figure 3.9 shows when $\overline{F}$ =180 and $\overline{P_{G2}}$ =50MW, Generator 2 can select the bidding variable arbitrarily not larger than the $k_{G2\max}^{(c)}$. However, the output of Generator 1 and Generator 2 are unchanged after 20 generations as shown in Figure 3.10.

As shown in Figure 3.8, one pure NE (Point D) in the continuum is converged stochastically in the proposed algorithm in this case. The NE continuum also exists in LSFE under *a*-parametrization and *b*-parametrization with generation capacity constraint $\overline{P_{G2}}$ =50MW.

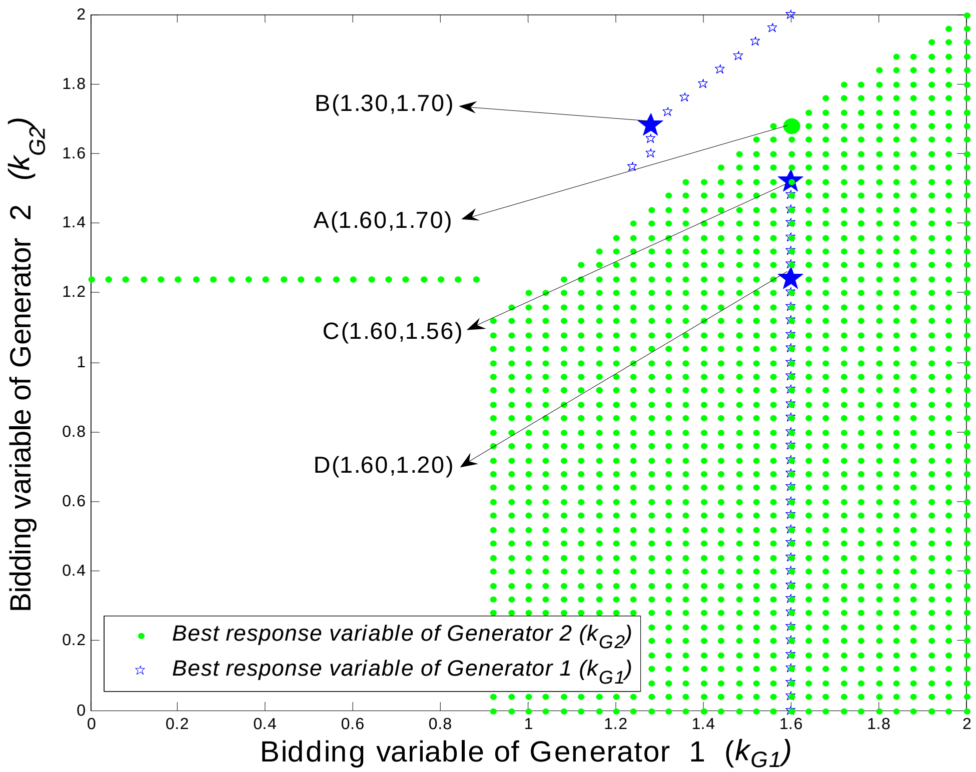

Figure 3.8: Best response curves for $\overline{F}$ =180MW and $\overline{P_{G2}}$ =50MW.

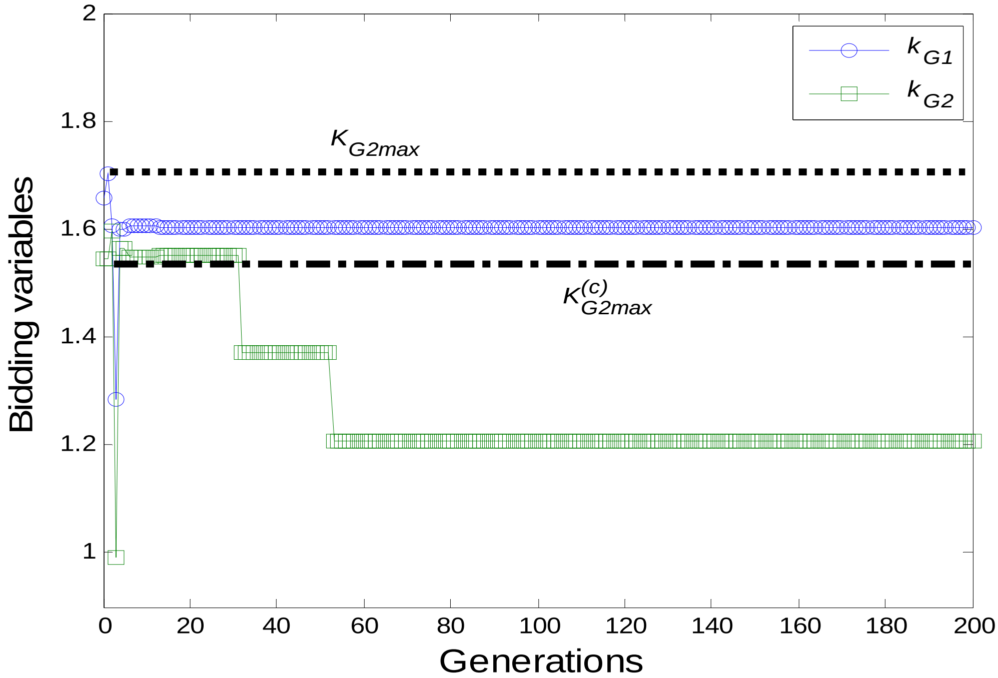

Figure 3.9: Evolution process of bidding variables for $\overline{F}$ =180MW and $\overline{P_{G2}}$ =50MW.

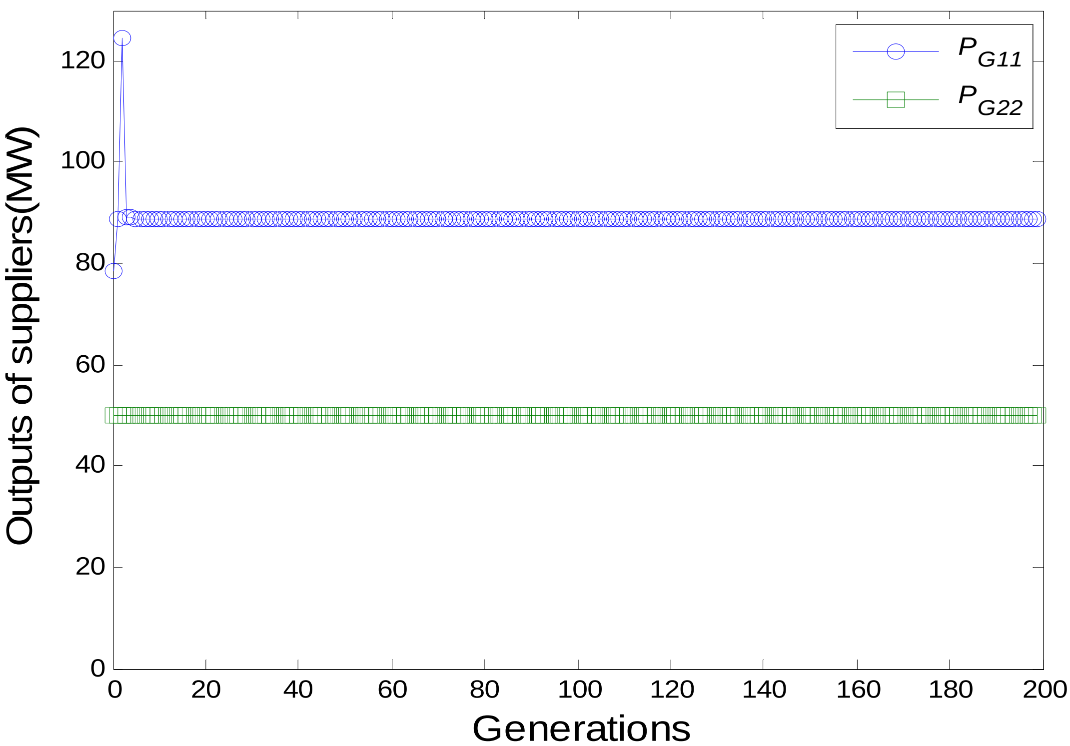

Figure 3.10: Evolution process of output for $\overline{F}$ =180MW and $\overline{P_{G2}}$ =50MW.

C Simulation results:

In this section, the impact of transmission and generation capacity constraints on the behavior of generators are also investigated. LSFE with different supply function parameters and Cournot model are tested. The upper and lower limits of bidding variable are assumed to be a_i*20, b_i*20, 20 and 0, 0, 0 in LSFE under *a*-parametrization, *b*-parametrization and $(a \propto b)$ -parametrization respectively. The upper and lower limits of α_i and β_i are assumed to be a_i*10^6 and - a_i*10^6, b_i*10^6 and -b_i*10^6 in LSFE under (a,b) -parametrization test cases respectively.

The following four cases are studied:

Case A: $\overline{F}$ =180MW

Case B: $\overline{F}$ =80MW

Case C: $\overline{F}$ =180MW and $\overline{P_{G2}}$ =50MW

Case D: $\overline{F}$ =80MW and $\overline{P_{G2}}$ =50MW

The simulation results of different cases are shown in Table 3.3. It shows that the profits of the GenCos are more than the profits in the competitive case because each GenCo can exercise its market power through the strategic bidding to yield higher price and profit in Case A. The results of different LSFE types depend on the method of parametrization greatly. Different LSFE parametrization will result in different solutions. How to select the proper coefficients for the LSFE is very important in market analysis.

The market may have no pure NE in LSFE under *a*-, *b*-, and $(a \propto b)$ -parametrization if the transmission line is tight ($\overline{F}$ =50MW) as shown in Case B. However, when the generators also have tighter generation capacity constraints, the system can have a pure NE due to the change of power flow pattern as shown in Case D.

Basing on the comparisons between Cases A and C, the market price increases due to the generation capacity constraints. For example, in Case C, if the power output of Generator 2 reaches its upper limit, Generator 1 can withhold some generating abilities to lead the shortage of power supply and lifts up the market price. The market has a NE continuum due to the capacity constraints.

In the LSFE under (a, b) -parametrization simulation cases, i.e. Cases A, B, C and D, the slope and intercept of supply functions are not unique, but the market-clearing price and the generators' outputs are unique and equal to the results of the Cournot model in Cases A, B, C and D respectively.

In these cases, the slope of the supply function is a very large positive value and the intercept is a very large negative value when the capacity constraints are not hit. Since the slopes become large, the generators become less competitive and their bidding behaviors are similar to that of Cournot quantity decision makers. A focal equilibrium [95] is found under (a, b) -parametrization because it is mutually beneficial to all the strategic generators in Case A. The simulation results demonstrate that it can also converge to the focal equilibrium in tighter capacity and transmission constrained markets in Cases B, C and D.

When Generator 2 hits its capacity constraint, its output cannot be changed. Its behavior is similar to that of a Cournot quantity decision price maker. As there are only two generators in the system, the residual demand is provided by the Generator 1 only.

The bidding behaviors of Generator 1 and the quantity decision market price maker are also alike. The outcomes of LSFE in Cases C and D are close to that of the Cournot model. Tight generation capacity constraint may make LSFE market equilibrium approach to Cournot market equilibrium.

Table 3.3: Case study results of 2-bus test system

Results	Case A					
	Perfect comp.	LSFE under a-para.	LSFE under b-para.	LSFE under $(a \propto b)$-para.	LSFE under (a,b)-para	Cour.
α_1 or β_1 or k_{G1}	--	0.0512	11.633	1.1502	--	--
α_2 or β_2 or k_{G2}	--	0.0512	11.632	1.1502	--	--
P_{G11}(MW)	111.11	94.68	102.02	101.08	76.92	76.92
P_{G22} (MW)	111.11	94.68	102.07	101.08	76.92	76.92
π_1($/h)	123.46	369.63	270.64	284.71	532.54	532.54
π_2($/h)	123.46	369.63	270.72	284.71	532.54	532.54
p_1($/MWh)	12.22	14.85	13.67	13.83	17.69	17.69
p_2($/MWh)	12.22	14.85	13.67	13.83	17.69	17.69
Results	Case B					
	Perfect comp.	LSFE under a-para.	LSFE under b-para.	LSFE under $(a \propto b)$-para.	LSFE under (a,b)-para.	Cour.
α_1 or β_1 or k_{G1}	--	--	--	--	--	--
α_2 or β_2 or k_{G2}	--	--	--	--	--	--
P_{G11}(MW)	80.00	--	--	--	76.92	76.92
P_{G22}(MW)	136.00	--	--	--	76.92	76.92
π_1($/h)	64.00	--	--	--	532.54	532.54
π_2($/h)	184.96	--	--	--	532.55	532.54
p_1($/MWh)	11.60	--	--	--	17.69	17.69
p_2($/MWh)	12.72	--	--	--	17.69	17.69
Results	Case C					
	Perfect comp.	LSFE under a-para.	LSFE under b-para.	LSFE under $(a \propto b)$-para.	LSFE under (a,b)-para	Cour.
α_1 or β_1 or k_{G1}	--	0.1000	17.111	1.6038	--	--
α_2 or β_2 or k_{G2}	--	*	*	*	--	--
P_{G11}(MW)	160.00	88.89	88.89	88.89	88.89	88.89
P_{G22} (MW)	50.00	50.00	50.00	50.00	50.00	50.00
π_1($/h)	256.00	711.11	711.11	711.11	711.11	711.11

π_2($/h)	135.00	419.44	419.44	419.44	419.44	419.44
p_1($/MWh)	13.20	18.89	18.89	18.89	18.89	18.89
p_2($/MWh)	13.20	18.89	18.89	18.89	18.89	18.89
	Case D					
Results	Perfect comp.	LSFE under a-para.	LSFE under b-para.	LSFE under $(a \propto b)$-para.	LSFE under (a,b)-para.	Cour.
α_1 or β_1 or k_{G1}	--	0.120	18.000	1.6897	--	--
α_2 or β_2 or k_{G2}	--	*	*	*	--	--
P_{G11}(MW)	80.00	80.00	80.00	80.00	80.00	80.00
P_{G22}(MW)	50.00	50.00	50.00	50.00	50.00	50.00
π_1($/h)	64.00	704.00	704.00	704.00	704.01	704.00
π_2($/h)	455.00	455.00	455.00	455.00	455.00	455.00
p_1($/MWh)	11.60	19.60	19.60	19.60	19.60	19.60
p_2($/MWh)	19.60	19.60	19.60	19.60	19.60	19.60

Notes:

1. '*' means that the bidding variable is not unique and there exist a continuum.

2. The bold characters mean that the capacity constraint of the generator is hit.

3.3.2 IEEE 30-Bus Test System

A modified IEEE-30 bus system from [96] is applied in this example. The IEEE 30-bus test system has 30 buses, 41 lines, 6 generators and 21 loads. The transmission data can be obtained in [96]. The 6 generators belong to two GenCos. Generators 1 , 2, 3 on buses 1, 2 and 5 respectively belong to GenCo 1 and Generators 4, 5, 6 on buses 8, 11 and 13 respectively belong to GenCo 2. Tight transfer limits are assumed in the transmission line between buses 1 and 3，2 and 4, 2 and 6, 5 and 7 (branch 2, 3, 6 and 8 in [96] respectively). The upper and lower limits of all bidding variables are same as the cases in the 2-bus test system respectively. The coefficients of generators' cost function are given in Table 3.4. The demand curve of each demand is $p_i = 45 - d_i P_{Di}$ where d_i is chosen such that $p_i = 35$ ($/MWh) for the assumed value of P_{Di} in [96]. The demand constraints are $\underline{P_{Di}}$ =0MW and $\overline{P_{Di}} = 45/d_i$ MW.

Table 3.4: Coefficients of generators' cost function

Generator No.	Bus No.	a_i ($/(MW)^{2}h)	b_i ($/MWh)	c_i ($/h)	$\underline{P_{Gi}}$ (MW)	$\overline{P_{Gi}}$ (MW)
1	1	0.075	20	0	50	200
2	2	0.35	17.5	0	20	80
3	5	1.25	10	0	15	50
4	8	0.1668	32.5	0	10	35
5	11	0.5	30	0	10	30
6	13	0.5	30	0	12	40

The following three cases are studied:

Case A: the transmission constraints of all branches are equal to the original data in [96]

Case B: the transmission constraints of branches 2, 3, 6 and 8 are 50% of the original data

Case C: the transmission constraints of branches 2, 3, 6 and 8 are 20% of the original data

The simulation results are shown in Table 3.5. The results of LSFE under $(a \propto b)$-parametrization are similar to that of *a*-parametrization and *b*-parametrization in Cases A and C. Besides, no pure NE is found in Case B due to transmission constraints. Therefore, these results are not shown. In Cases A and C, there may exist a NE continuum because generators hit their generation capacity constraints. The algorithm can converge to one pure NE stochastically.

As shown in Table 3.5, the market price in LSFE competition is higher than that in perfect competition in Cases A and C respectively. In the LSFE under

(a, b) -parametrization in Cases A and C, the slope and intercept of supply functions are not unique, but the market-clearing price and the generators' outputs are unique and equal (except the minor difference) to the results of the Cournot model in Cases A and C respectively. It means that a focal equilibrium is converged. The minor numerical difference of solutions in Table 3.5 is mainly due to the limits of $10^{\wedge 6}$ order for the limits of supply function parameters α_i and β_i. The numerical difference will be reduced when larger limitation values of supply function parameters are used.

The transmission constraint can make the difference of nodal price in Case C. Generators 4, 5 and 6 can generate more power so GenCo 2 gets more profit. The profit of GenCo 1 decreases because transmission constraints make its generators (Generators 1, 2 and 3) impossible to generate more power. Due to different locations in the network, some generators can increase their outputs for getting higher profits due to the congestion; and the other generators may lose some market power and get lower profits. Therefore, it is clear that the generators may not increase their profits for the cases of congestion.

Because transmission constraints and generation capacity constraints make generators become less competitive, the solutions of different parametrization LSFE are similar to Cournot model in Cases A and C. When the transmission constraints become tighter, the market power becomes more serious in Case C. It can be observed that the obtained results and phenomena of this test system are consistent with that of the 2-bus system.

Table 3.5: Case study results of IEEE 30-bus test system

Results	Case C			
	Perfect comp.	LSFE under $(a \propto b)$-para.	LSFE under (a,b)-para.	Cour.
k_{G1}	--	1.1848	--	--
k_{G2}	--	1.1915	--	--
k_{G3}	--	1.2123	--	--
k_{G4}	--	1.0268	--	--
k_{G5}	--	*	--	--
k_{G6}	--	*	--	--
P_{G11}(MW)	193.3829	144.7677	136.5854	136.3446
P_{G22}(MW)	48.7485	37.6687	36.2161	36.3362
P_{G35}(MW)	19.6448	16.1261	15.9037	16.1773
P_{G48}(MW)	12.2750	18.5977	17.8328	17.8193
P_{G511}(MW)	10.0000	10.0000	10.9451	10.8954
P_{G613}(MW)	12.0000	12.0000	12.0000	12.0000
π_1($10^{\wedge 3}$\$/h)	2.0595	2.3469	2.3518	2.3523
π_2($10^{\wedge 3}$\$/h)	0.0516	0.1299	0.1443	0.1441
p_1 (\$/MWh)	34.5037	36.5601	36.9016	36.8984
p_2 (\$/MWh)	34.562	36.5601	36.9016	36.8984
p_5(\$/MWh)	34.5560	36.5601	36.9016	36.8984
p_8 (\$/MWh)	34.5499	36.5601	36.9016	36.8984
p_{11}(\$/MWh)	34.5493	36.5601	36.9016	36.8984
p_{13}(\$/MWh)	34.5477	36.5601	36.9016	36.8984

Results	Case C			
	Perfect comp.	LSFE under $(a \propto b)$-para.	LSFE under (a,b)-para.	Cour.
k_{G1}	--	1.6148	--	--
k_{G2}	--	*	--	--
k_{G3}	--	1.2482	--	--
k_{G4}	--	1.0922	--	--
k_{G5}	--	1.1027	--	--
k_{G6}	--	*	--	--
P_{G11}(MW)	98.4109	58.1776	56.6242	57.0328
P_{G22}(MW)	24.8167	20.0000	20.0000	20.000
P_{G35}(MW)	22.0147	17.4258	17.6490	17.7344
P_{G48}(MW)	35.0000	25.4502	23.7169	23.7633
P_{G511}(MW)	19.4192	12.7261	13.4194	13.3774
P_{G613}(MW)	16.6885	12.0000	14.7066	14.5566
π_1($10^{\wedge 3}$\$/h)	0.7739	1.6896	1.6586	1.6857
π_2($10^{\wedge 3}$\$/h)	0.3326	0.3122	0.3120	0.3125
p_1 (\$/MWh)	27.3808	39.3419	39.9931	39.4656
p_2 (\$/MWh)	26.1858	39.2013	39.9729	39.3655

p_5($/MWh)	37.5184	39.6706	39.9238	39.6996
p_8 ($/MWh)	40.2413	40.1386	39.9443	40.0328
p_{11}($/MWh)	39.7096	40.0976	39.9568	40.0036
p_{13}($/MWh)	38.3443	39.9923	39.9931	39.9287

Notes:

1. '*' means that the bidding variable is not unique and there may exist a continuum.

2. The bold characters mean that the capacity constraint of the generator is hit.

3.4 Conclusion

This chapter has successfully applied CGA to determine the market equilibrium in electricity market with generation capacity and transmission constraints under the LSFE model and the Cournot model.

The simulation results show that the LSFE under (a,b)-parametrization converges to a focal equilibrium that is equal to Cournot equilibrium under the capacity and transition transmission constraints in all cases. The simulation results have also shown that the system may not have a pure equilibrium due to the transmission congestion. But an equilibrium continuum may exist when the generation capacity of generators becomes tighter in LSFE under *a*-, *b*- and $(a \propto b)$-parametrization. The solutions of market power analysis are different and depending on the parameters selected in different types of LSFE. It is also demonstrated that when these constraints are hit, the market price will increase and the abuse of market power can become more serious. Tighter constraints lead the solution of LSFE under *a*-, *b*- and $(a \propto b)$-parametrization close to the solution of Cournot model.

The results also show that Cournot prices are possible outcomes in the markets where bids can be changed in one pricing period (i.e. an hour). These observations should be contrasted with the multiple pricing period models. The requirement to bid consistently across a time horizon may limit the exercise of market power in above multiple pricing-period models. It is important to study electricity market in multiple pricing period market.

CHAPTER 4 MULTI-PERIOD MARKET SIMULATION AND ANALYSIS

4.1 Introduction

In the study of Chapter 3, a supply function is specified for each hour-long pricing period. Recently, some studies have been performed on determination of the market equilibrium with LSFE in a single pricing period [34-36]. This assumption is reasonable in several BBP markets, such as England and Wales market after 2001 and California power market. However, this assumption is not a feature of all BBP markets. In several BBP markets, such as the England and Wales market until 2001 and PJM market (PJM interconnection is a regional transmission organization that coordinates the movement of wholesale electricity in all or parts of Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia and the District of Columbia), a single supply function is applied across multiple pricing period. Green and Newbery [25] model each player by specifying a single supply function bid that is applied to all pricing period over an extended length of time. This assumption will be investigated in this chapter.

Baldick and Hogan show that SFE prices will be below Cournot prices if it is constant through a time horizon [91]. The market outcome of a supply function across all pricing period should be compared with that of the supply function in a single pricing period, and whether it can give important information to market regulators and policy makers should be studied. It is also important to find a bidding rule for the regulator and whether it is useful to relieve the market power.

Compared to actual markets, most of these studies have not considered the inter-temporal constraints of the real market. But the regulators and market participants need a new methodology to analyze market power and bidding strategies in multiple pricing period market. It is desirable for market simulation to reproduce as close as possible the actual market functioning to make the simulator results comparable to actual market settings. Many researches have also paid attention to bidding behavior of GenCos and Unit Commitment (UC) problem in a market environment [97]. Multi-period electricity auction market simulation method that explicitly takes into account transmission congestion as well as inter-temporal operating constraints such as start-up costs, ramp rates etc is presented in [98, 99].

To determine the market equilibrium is generally modeled as an EPEC, such as transmission line constraints and capacity constraints, are considered. It will become more complex to model the effect of the actual GenCos on market-clearing prices in multi-period market setting considering the inter-temporal constraints. Co-evolutionary computation approach has successfully used to economical simulation [33, 55-58] and it will be employed as an alternative tool to simulate the complex electricity market game.

The purpose of this chapter is to provide a co-evolutionary computation approach to simulate a day-ahead BBP electricity market in which GenCos are with capacity and inter-temporal constraints. The outcomes of a market in which GenCos use the supply functions being constant or non-constant across multiple pricing period are studied and compared.

4.2 Market Model Formulation

Suppose there are *I* GenCos, each has a thermal unit (i.e. generator), in the test system. The GenCo is assumed to submit a bid for its unit to the ISO, in the form of LSF, including the intercept and slope of the LSF. Each unit is assumed to have a strictly concave quadratic cost function:

$$C_i\left(P_{Gi}(t)\right) = \frac{1}{2} a_i P_{Gi}{}^2(t) + b_i P_{Gi}(t) + c_i \quad i = 1, \ldots, I \tag{4.1}$$

where I is number of units; $P_{Gi}(t)$ is power generated by unit *i* at time *t*; $C_i(P_{Gi}(t))$ is fuel cost of unit *i* for generating power at time *t*; a_i, b_i and c_i are unit *i* cost coefficients.

The marginal cost function is affine for each unit as follows:

$$\frac{dC_i}{dP_{Gi}}\left(P_{Gi}(t)\right) = a_i P_{Gi}(t) + b_i \quad i = 1, \ldots, I \tag{4.2}$$

It is assumed that the system demand has an inverse linear demand function and the transmission loss is negligible. Then the system demand at pricing period *t* will be equal to the total output of all the units in the market as shown below:

$$P_S(t) = \overline{P_S(t)} - rp(t) = \sum_{i=1}^{I} P_{Gi}(t) \quad i = 1, \ldots, I \tag{4.3}$$

where $P_S(t)$ is system demand at time *t*; r and $\overline{P_S(t)}$ are coefficients of demand function at time *t*, r is the slope of demand function and $\overline{P_S(t)}$ is the forecasted demand at time *t*.

If $r \neq 0$, the system demand benefit function can be represented by:

$$B(P_s(t)) = -\frac{1}{2r}P_s^2(t) + \frac{1}{r}\overline{P_S(t)}P_s(t) \tag{4.4}$$

$B(P_s(t))$ is the benefit of system demand at *t*.

The GenCos need to provide their bids to the power market with an inverse LSF form as follows.

$$p(t) = \alpha_i(t)P_{Gi}(t) + \beta_i(t) \quad i = 1, \dots, I \tag{4.5}$$

where α_i and β_i are LSF coefficients.

In a day-ahead power market, the GenCos submit the bidding sets to the ISO. The transactions are determined by the UC and Economic Dispatch (ED). The UC optimization problem can be formulated as the following mixed integer programming problem. The ISO optimization problem is formulated as to minimize total fuel cost (i.e. (4.6)) or to maximize the summation of social welfare (i.e. (4.7)) when the slope of the demand function is equal to zero or not respectively.

$$Min \quad F = \sum_{t=1}^{T}\left\{\sum_{i=1}^{I}U_i(t)\left(\frac{1}{2}\alpha_i(t)P_{Gi}{}^2(t) + \beta_i(t)P_{Gi}(t)\right) + S_i(x_i(t-1), U_i(t))\right\} \tag{4.6}$$

$$\begin{aligned} Max \quad \Gamma_{ISO} = &\sum_{t=1}^{T}\left(-\frac{1}{2r}P_s^2(t) + \frac{1}{r}\overline{P_S(t)}P_s(t)\right) \\ &- \sum_{t=1}^{T}\left\{\sum_{i=1}^{I}U_i(t)\left(\frac{1}{2}\alpha_i(t)P_{Gi}{}^2(t) + \beta_i(t)P_{Gi}(t)\right) + S_i(x_i(t-1), U_i(t))\right\} \end{aligned} \tag{4.7}$$

$$s.t. \qquad \sum_{i=1}^{I} P_{Gi}(t)U_i(t) = P_s(t) \quad \text{energy balance} \tag{4.8}$$

$$\sum_{i=1}^{I} \overline{P_{Gi}} U_i(t) \geq R(t) + P_S(t) \quad \text{spinning reserve} \tag{4.9}$$

$$\underline{P_{Gi}} \leq P_{Gi}(t) \leq \overline{P_{Gi}} \quad \text{capacity constraint} \tag{4.10}$$

$$\begin{array}{ll} U_i(t) = 1 \quad if \quad 1 \leq x_i(t) \leq \overline{\tau_i} & \text{min up time} \\ U_i(t) = 0 \quad if \quad -\underline{\tau_i} \leq x_i(t) \leq -1 & \text{min down time} \end{array} \tag{4.11}$$

where T is time horizon; $x_i(t)$ is state of unit *i* at time t, denoting number of hours that the unit has been on (positive) or off (negative); $U_i(t)$ is decision variable of unit *i* at time t, 1 for up, 0 for down; $S_i(x_i(t-1), U_i(t))$ is start-up cost of unit *i* at time *t*; $R(t)$ is system spinning reserve.

The GenCos' optimization problem can be formulated as (4.12) and the decision variable are $\alpha_i(t)$ and $\beta_i(t)$.

$$Max \quad \pi_i = \sum_{t=1}^{T} (\, p(t)P_{Gi}(t) - C_i(P_{Gi}(t)) - S_i(x_i(t-1), U_i(t))\,) \tag{4.12}$$

So (4.6)-(4.12) formulate a two-level optimization problem. The first level optimization problem is UC and ED optimization problems determined by ISO; and the second level optimization problem is each market GenCo to maximize its profit. This equilibrium model can be categorized as an EPEC.

4.2.1 Single pricing period market model

First the minimum up and down time constraints and start-up cost are not considered and all units must be turned on in each pricing period. The ISO optimization problem formulated in (4.7) can be reformed as (4.13) in each pricing period.

$$Max \quad \Gamma_{ISO}(t) = -\frac{1}{2r} P_s^2(t) + \frac{1}{r} \overline{P_S(t)} P_s(t) - \sum_{i=1}^{I} \left(\frac{1}{2} \alpha_i(t) P_{Gi}{}^2(t) + \beta_i(t) P_{Gi}(t) \right) \tag{4.13}$$

The optimization problem of the GenCo *i* in each pricing period *t* is formulated as:

$$\begin{aligned} \pi_i(t) &= p(t) P_{Gi}(t) - C_i(P_{Gi}(t)) \\ &= p(t) \left(P_S(t) - \sum_{j \neq i} P_{Gj}(t) \right) - C_i \left(P_S(t) - \sum_{j \neq i} P_{Gj}(t) \right) \end{aligned} \tag{4.14}$$

Differentiating the profit with respect to price at time *t* yields:

$$\begin{aligned} \frac{d\pi_i(t)}{dp(t)} = &\left(P_S(t) - \sum_{j \neq i} P_{Gj}(t) \right) + \left(p(t) - C_i' \left(P_S(t) - \sum_{j \neq i} P_{Gj}(t) \right) \right) \\ &\times \left(\frac{dP_S(t)}{dp} - \sum_{j \neq i} \frac{dP_{Gj}(t)}{dp} \right) \end{aligned} \tag{4.15}$$

Setting this derivative to zero produces:

$$P_{Gi}(t) = \left(p(t) - C_i' \left(P_S(t) - \sum_{j \neq i} P_{Gj}(t) \right) \right) \times \left(-\frac{dP_S(t)}{dp} + \sum_{j \neq i} \frac{dP_{Gj}(t)}{dp} \right) \tag{4.16}$$

$P_{Gi}(t)$ will not be equal to zero in a single pricing period. If $P_{Gi}(t)$ is equal to zero, GenCo *i* will not satisfy its profit and will change its strategy. Then other GenCos will also change their strategies.

4.2.2 Multiple pricing period market model

The minimum up and down time constraints and start-up cost are not considered and all units must be turned on in each pricing period too. Assume the bid supply function must be consistent across all pricing period.

$$\begin{cases} \alpha_i(t) = \alpha_i(1) \quad t = 2, \ldots, T \\ \beta_i(t) = \beta_i(1) \end{cases} \tag{4.17}$$

This assumption matches with several markets, such as England and Wales until 2001 and markets in the Eastern United States such as PJM.

If $P_{Gi}(t)$ is not equal to zero, (4.12) can be differentiated with respect to $p(t)$.

$$\frac{d\pi_i}{dp(t)} = \frac{d[\sum_{t=1}^{T} \pi_i(t)]}{dp(t)} = \frac{d\pi_i(t)}{dp(t)} \tag{4.18}$$

Setting this derivative to zero, (4.16) is also obtained. Because the bid supply functions are consistent across all times, these equations must be satisfied at every realized value of price *p*. Therefore, (4.19) can be obtained under this assumption [30] .

$$\begin{cases} \beta_i(t) = b_i & i = 1, \ldots, I, \quad t = 1, \ldots, T \\ \alpha_i(t) = \dfrac{1}{(r + \sum_{i=1, j \neq i}^{I} \frac{1}{\alpha_j})} + a_i & \end{cases} \tag{4.19}$$

In a low demand period, if $P_{Gi}(t)$ is equal to zero, $p(t)$ is nonsensical to the profit of supplier *i*. Then profit function (4.12) cannot be differentiated with respect to $p(t)$. It means (4.16) (i.e. equation (4) in [26]) may not exist and (4.19) may not be obtained.

It is difficult to analyze the condition for the existence of market equilibrium when capacity constraints are considered. In this chapter, a co-evolutionary computation approach is employed to find the NE under these situations.

4.2.3 Market equilibrium with inter-temporal constraints

When the inter-temporal constraints are considered in the market clearing model, the GenCos' optimization problems defined in (4.12) are very complex. It is hard to acquire the NE by analytical methods, so the CGA is used as an alternative tool to market simulation.

The UC optimization problem is solved by Dynamic Programming (DP) methods. DP is characterized by the forward and back path operations. Commitment of units progresses one hour at a time, and combinations of schedulable units are stored for each hour. Finally, the most economical schedule is obtained by backtracking from the combination with the least total cost at the final hour through the optimal path to the combination at the initial hour. Thus if there are I schedulable units in an hour, then there are 2^I combinations to evaluate. Obviously, it is not practical to evaluate all of the combinations.

The Dynamic Programming-Sequential Combination (DP-SC) method [100] generates a subset of the combinations by turning each unit on in priority list sequence. Thus if there are I schedulable units, only I+1 combinations will be evaluated. Proper ordering of the units in the priority list is expected to yield more economic schedules. Generators with lower hear rate will be at higher priority. If generators have the same heat rate (same HR_i value), the one with higher capacity ($\overline{P_{Gi}}$) will be of higher priority. The calculation for HR is given:

$$HR_i = \frac{C_i(\overline{P_{Gi}})}{\overline{P_{Gi}}} \quad i = 1, \ldots, I \tag{4.20}$$

Since many combinations are neglected, the optimal path may not be found. This technique seems to be well suited when the system load is changing rapidly. DP-SC method is presented in [100].

4.3 Co-evolutionary Approach to Analyzing Market Equilibrium

The basic cooperative coevolution model is given in this Chapter 2. The co-evolutionary computation model can be regarded as a special form of the Agent-based Computational Economics (ACE) model [101]. ACE is a computational study of economies modeled as dynamic systems of interacting agents. The ability of ACE to capture the independent decision-making behavior and interactions of individual agents provides a very good platform for the modeling and simulation of electricity markets. Each GenCo in the market under investigation is represented by an agent in the model.

The co-evolutionary algorithm comprises multiple species (i.e. agents). Each agent represents a GenCo in the market. The agents interact with one another within a shared domain model. The market clearing problem is modeled in the domain model.

In the algorithm, agents can calculate their best strategies based on information about what other agents have done in the last generation [79]. Individuals in the agents with higher fitness are at a productive advantage compared to individuals with low fitness, hence the latter decrease in frequency in the population over time. When there exists a pure NE, the algorithm can find it efficiently [33, 56]. Each species has no incentive to change it strategy to get a higher fitness when the algorithm gets to the pure NE. When there is no pure NE, the algorithm could not find a stable strategies set. It means the algorithm could not find a strategy set that all the players satisfy their profits. The algorithm can find a Pareto solution under this condition [73].

The proposed approach is implemented using a real-coded GA. A decision variable x_i is represented by a real number within its lower limit *Lb* and its upper limit *Ub*, i.e. $x_i \in [Lb, Ub]$. The crossover and mutation operators are described as follows [102]:

Crossover:

A blend crossover operator has been employed in the study. This operator generates the offspring randomly from the interval $[x_i - \tau(y_i - x_i), y_i + \tau(y_i - x_i)]$, where x_i and y_i are the decision values of the parent solutions and $x_i < y_i$. τ is a random number between 0 and 1. To ensure the balance between exploitation and exploration of the search space $\tau = 0.5$ is selected.

Mutation:

A dynamical non-uniform mutation operator to reduce the disadvantage of random mutation in the real-coded GA is used and defined as follows:

$$x_i^{'} = \begin{cases} x_i + \Delta(t, UB - x_i) & \text{if random } \tau \text{ is } 1 \\ x_i - \Delta(t, LB - x_i) & \text{if random } \tau \text{ is } 0 \end{cases} \tag{4.21}$$

where x_i and $x_i^{'}$ are the selected and resultant values respectively for the mutation; t is generation number of CGA. The function $\Delta(t, y)$ returns a value in the range [0, y] such that $\Delta(t, y)$ approaches to zero as t increases. This property causes this operator to search the space uniformly in the initial stages (i.e. when t is small), and locally at later stages. This strategy increases the probability of generating a new number close to its successor than a random choice. The following function is used:

$$\Delta(t, y) = y(1 - \sigma^{(1-\frac{t}{T})^{\delta}}) \tag{4.22}$$

where σ is a uniform random number from [0, 1], T is the maximal generation number, and δ is a system parameter determining the degree of dependency on the iteration number. In order to prevent the algorithm from stalling or premature convergence, it needs to explore the search space when the generations become large. So δ =1 is used to replace the generally used δ =5.

Fitness scaling technical is also employed to improve performance of the algorithm.

Fitness scaling：

At the start of GA runs, it is common to have a few individuals of extraordinary fitness, while the rest of the population has mediocre fitness. If left to normal selection, these few extraordinary strings will take over a significant proportion of the finite population. This usually leads to premature convergence. There is another problem that occurs quite late in the runs. The population average fitness may be close to the best fitness of population. And the survival of the fittest which is so important for improvement across generations just becomes a random walk among the mediocre. In both cases, fitness scaling can be helpful. A fitness scaling technique based on simulated anneal technique is given:

$$f_j^{'} = e^{f_j / T_{em}} \tag{4.23a}$$

$$T_{em} = T_{em}^{0}(0.99^{t-1}) \tag{4.23b}$$

where T_{em}^{0} is initial temperature; T_{em} is the temperature; f_j is fitness of individual j; $f_j^{'}$ is scaled fitness of individual j;

The flow chart of CGA is shown in Figure 4.1.

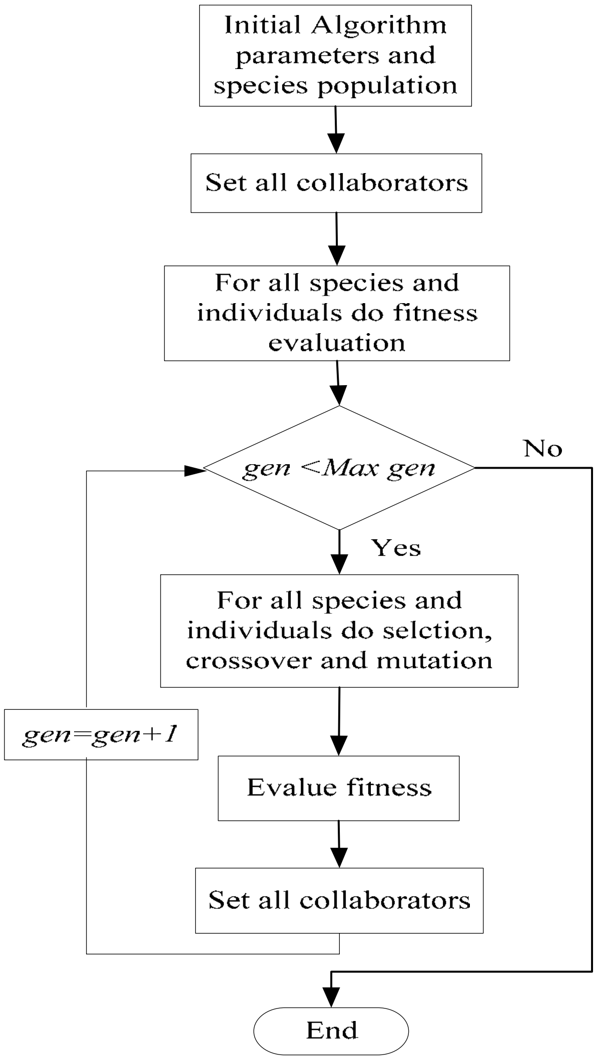

Figure 4.1: Flow chart of the CGA

4.4 Case Study

In this chapter, the proposed method is applied to revised IEEE 6 generators test system [103]. The 6 generators belong to 6 GenCos respectively. The CGA parameters are given in Table 4.1 and each generation contains 2 nested generations of evolution of each species.

Table 4.1: CGA parameters

Parameters	Description
Variable code type	Real code
Initial population	Randomly initialized population
Population size	40
Max. generation	300
Mutation	Non-uniform mutation(mutation probability= 0.05, δ =1)
Crossover	Blend crossover (crossover probability= 0.9)
Selection	Roulette selection with fitness scaling (T_{em}^{0} =500) and 5% population are elitism

Load demand data is shown in Table 4.2.

Table 4.2: Load demands for 24 hours

Hour	$\overline{P_s(t)}$(MW)	Hour	$\overline{P_s(t)}$(MW)	Hour	$\overline{P_s(t)}$(MW)
1	166	9	192	17	246
2	196	10	161	18	241
3	229	11	147	19	236
4	267	12	160	20	225
5	283.4	13	170	21	204
6	272	14	185	22	182
7	246	15	208	23	161
8	213	16	232	24	131

The coefficient of 6 generators study cases are given in Table 4.3.

Table 4.3: Coefficients of GenCos

GenCos No.	1	2	3	4	5	6
$\underline{P}_{Gi}$ (MW)	50	20	15	10	10	12
$\overline{P}_{Gi}$ (MW)	200	80	50	35	30	40
a_i (10^{-2}\$/(WM)^{2}h)	0.75	3.5	12.5	1.668	5.0	5.0
b_i(\$/(WM)h)	2	1.75	1	3.25	3	3
c_i(\$)	0	0	0	0	0	0
Min up time(Hr)	1	2	1	1	2	1
Min down time(Hr)	1	2	1	2	1	1
Init unit status	1	3	2	3	2	2
Start cost ($)	123.0	130.5	81.5	188.5	126.0	76.5

The study cased and simulation results are showed in Tables 4.4 and 4.5.

Case A_1: single pricing period LSFE model

Case B_1: single pricing period Cournot model

Case C_1: single pricing period LSFE with capacity constraints.

Case D_1: single pricing period Cournot model with capacity constraints.

Case E_1: multi pricing period LSFE model

Case F_1: multi pricing period LSFE with true cost coefficient β_i and capacity constraints.

Case G_1: multi pricing period LSFE with true cost coefficient β_i and inter-temporal constraints.

Cases A_2, B_2, C_2, D_2, E_2, F_2 and G_2 using same data but the loads increase 80MW in each pricing period comparing to Cases A_1, B_1, C_1, D_1, E_1, F_1 and G_1 respectively.

The load elastic is r=5 MW/$ in all pricing period. The study cases with reserve requirement ($R_s(t)=0.1P_s(t)$)are studied in Cases G_1 and G_2.

In the single period LSFE simulation cases, i.e. Cases A_1, C_1, A_2 and C_2, the slope and intercept of supply functions are not unique, but the market price and the GenCos' outputs are unique and equal to the results of the Cournot model in Cases B_1, D_1, B_2 and D_2 respectively. The minor numerical difference of solutions in Table III is mainly due to the limits of $10^{\wedge 4}$ order for the limits of supply function parameters α_i and β_i. The numerical difference will be reduced when larger limitation values of supply function parameters are used. In these cases, the slope of the supply function is a very large positive value and the intercept is a very large negative value when the capacity constraints are not hit. The simulation results demonstrate that it can converge to the focal equilibrium which equal to Cournot NE [33, 34].

By comparing Case $A_1$with C_1, when there has upper capacity constraint, the market price is rising and GenCos can have more market power in the peak demand pricing period (i.e. hour 5). Because some GenCos hit the upper capacity constraints, it leads to high price as shown in Figure 4.2. Due to the same reason, the market price in the peak demand periods (i.e. hours 3-8 and 15-21) with capacity constraints is higher than that without capacity constraints by comparing Cases $A_2$with C_2 as shown in Figure 4.4.

The market price is higher in the case that the GenCos without lower capacity constraints than that in the case with lower capacity constraints by comparing Cases A_1 and C_1 in hours 1-4 and 6-24. In these hours, the system demand is low and output of some GenCos is also very low because they have no lower capacity constraints in Case A_1. It means that the GenCos can withhold their output to uplift the market price, so the market price is higher in Case A_1 than in Case C_1 in these hours respectively. Due to the same reason, the market price will be higher in hours 1, 3-8 and 15-21 in Case A_2 than that in Case C_2.

In Case G_2, the bidding variable of β_i is equal to b_i.This result is equal to that the GenCos are assumed to bid β_i honestly. The seemingly simple result is important since no other strategic hypothesis is imposed but the general genetic operators on the GenCos' strategic learning, and only the multiple pricing period bidding requirement settles the supply functions down on a unique equilibrium. This is a key notion of SFE theories [30] .

In another multiple period Case G_1, the bidding variable of β_i is not equal to b_i because the output of some GenCos is equal to zero in several valley load periods, such as in hours 10-12 and 24. Although β_i is not equal to b_i exactly, it is close to b_i as shown in Table 4.4.

The NE existence and uniqueness condition is very hard to be obtained in a multiple pricing period market with capacity constraint. There may be multiple equilibriums. Simulation results show there exists multiple equilibriums. The algorithm can converge to one pure NE stochastically in each run.

Some of these equilibriums are Pareto efficient [84]. In these equilibriums, the GenCos hold their output and lift the market prices which are close to the Cournot market prices emerging in a single pricing period market. While the others aren't Pareto efficient, the outcome of the market is close to the outcome of the market in which the GenCos are assumed to bid β_i honestly. Baldick and Hogan use the stability theory to analyze the multiple pricing period market and point out only the equilibria that are

Table 4.4: Simulation results of low demand cases

Case	A_1	B_1	C_1	D_1	E_1	F_1	G_1
α_1/a_1	--	--	--	--	1.9091	2.6209	--
α_2/a_2	--	--	--	--	1.1252	1.2726	--
α_3/a_3	- --	--	--	--	1.0253	1.0658	--
α_4/a_4	--	--	--	--	1.4171	1.4833	--
α_5/a_5	--	--	--	--	1.1154	1.1463	--
α_6/a_6	--	--	--	--	1.1131	1.1452	--
β_1/b_1	--	--	--	--	1.0936	1.0000	--
β_2/b_2	--	--	--	--	1.0515	1.0000	--
β_3/b_3	--	--	--	--	1.0498	1.0000	--
β_4/b_4	--	--	--	--	0.9999	1.0000	--
β_5/b_5	--	--	--	--	1.0007	1.0000	--
β_6/b_6	--	--	--	--	1.0010	1.0000	--
p(1)($/MWh)	7.5507	7.5571	6.6138	6.6277	3.3162	3.2813	--
p(2)($/MWh)	8.5367	8.5585	7.8163	7.8288	3.4773	3.5847	--
p(3)($/MWh)	9.6732	9.6875	9.1384	9.1542	3.6545	3.8006	--
P(4)($/MWh)	10.950	10.935	10.696	10.708	3.8585	4.0363	--
p(5)($/MWh)	11.531	11.580	11.670	11.674	3.9465	4.1466	--
P(6)($/MWh)	11.118	11.118	10.967	10.979	3.8853	4.0675	--
P(7)($/MWh)	10.244	10.139	9.7966	9.8330	3.7457	3.9061	--
p(8)($/MWh)	9.1357	9.1288	8.4992	8.5103	3.5685	3.7015	--
p(9)($/MWh)	8.4303	8.4201	7.6554	7.6687	3.4558	3.5550	--
p(10)($/MWh)	7.3889	7.3883	6.4199	6.4256	3.2893	3.2231	--
p(11)($/MWh)	6.9267	6.9207	5.6534	5.6554	3.2037	3.0593	--
p(12)($/MWh)	7.4007	7.4128	6.3774	6.3830	3.284	3.2115	--
P(13)($/MWh)	7.6913	7.6912	6.7751	6.7937	3.3377	3.3282	--
p(14)($/MWh)	8.1952	8.1395	7.3751	7.3883	3.4182	3.5001	--
P(15)($/MWh)	8.9677	8.9849	8.2987	8.3099	3.5417	3.6684	--
p(16)($/MWh)	9.7740	9.7291	9.2574	9.2792	3.6706	3.8193	--
p(17)($/MWh)	10.244	10.245	9.7950	9.8968	3.7457	3.9061	--
p(18)($/MWh)	10.076	10.076	9.6176	9.6327	3.7189	3.8752	--
P(19)($/MWh)	9.9084	9.9094	9.4018	9.4329	3.692	3.8441	--
p(20)($/MWh)	9.5389	9.5391	8.9782	8.9913	3.633	3.7758	--
P(21)($/MWh)	8.8334	8.8354	8.1154	8.1548	3.5202	3.6406	--
P(22)($/MWh)	8.0933	8.0946	7.254	7.2649	3.4021	3.4683	--
p(23)($/MWh)	7.5188	7.5292	6.4133	6.4245	3.2893	3.2231	--
p(24)($/MWh)	6.3808	6.3815	2.8000	2.8000	3.0925	2.6443	--
$\pi_1(10^{\wedge 3}\$)$	5.6503	5.6657	7.1242	7.1658	2.7184	2.6428	--
$\pi_2(10^{\wedge 3}\$)$	5.0735	5.0992	4.2858	4.3170	1.1394	1.2153	--
$\pi_3(10^{\wedge 3}\$)$	3.8615	3.8725	3.2612	3.2863	0.6187	0.6556	--
$\pi_4(10^{\wedge 3}\$)$	3.6122	3.6122	2.9203	2.9220	0.0842	0.1320	--
$\pi_5(10^{\wedge 3}\$)$	3.1544	3.1564	2.5559	2.5659	0.0788	0.1008	--
$\pi_6(10^{\wedge 3}\$)$	3.1632	3.1874	2.5918	2.6104	0.0789	0.0950	--

close to competitive market equilibria are stable [91]. Then the supply functions with true coefficient β_i are used in this chapter to study the multiple pricing period market.

The price curve of the multiple periods market is smoother compared to the price curve of a single period market because each GenCo considers not only benefit of the high demand periods but also benefit of the low demand periods. It will causes price of the high demand periods to be low and price of the low demand periods to be high as shown in Figures 4.2 and 4.4. And the market price in multiple pricing period is also lower than the price of single pricing period market respectively.

In Case G_1, there may be no pure NE, the algorithm could not find a strategy set that it is satisfied by all GenCos. The algorithm can get a Pareto optimal solution in each run. 20 Pareto solutions will be obtained by running the algorithm 20 times as shown in Figure 4.3. Although there is no pure NE in Case G_1, the market price is fluctuating in a small range except pricing period 1. In Case G_2, the system demand is very high and the algorithm can find a pure NE. The market price in Cases G_1 and G_2 are close to in Cases F_1 and F_2 and is lower that that in Cases D_1 and D_2 respectively because the GenCos are not dispatched if their bids are too high in Cases G_1 and G_2. Therefore, the market power abuse can be mitigated.

It is found that the requirement of consistent biding across multiple pricing period can generate lower market price and alleviate the exercise of market power. Since some electricity markets have been set up with an obligation for consistent bids while others have not, it is important to confirm that the impacts of market rule specification on the outcomes.

Table 4.5: Simulation results of high demand cases

Case	A_2	B_2	C_2	D_2	E_2	F_2	G_2
α_1/a_1	--	--	--	--	2.1879	2.6998	2.8434
α_2/a_2	--	--	--	--	1.1902	1.2499	1.2915
α_3/a_3	--	--	--	--	1.0448	1.0657	1.0710
α_4/a_4	--	--	--	--	1.4474	1.5085	1.4944
α_5/a_5	--	--	--	--	1.1328	1.1809	1.1858
α_6/a_6	--	--	--	--	1.1244	1.1861	1.2011
β_1/b_1	--	--	--	--	0.9941	1.0000	1.0000
β_2/b_2	--	--	--	--	0.9998	1.0000	1.0000
β_3/b_3	--	--	--	--	1.0092	1.0000	1.0000
β_4/b_4	--	--	--	--	1.0005	1.0000	1.0000
β_5/b_5	--	--	--	--	0.9985	1.0000	1.0000
β_6/b_6	--	--	--	--	1.0010	1.0000	1.0000
$p(1)$ (\$/MWh)	10.2107	10.2323	9.8062	9.8331	3.7639	3.9275	3.9699
$p(2)$ (\$/MWh)	11.3089	11.3206	11.2166	11.218	3.9358	4.1170	4.1787
$p(3)$ (\$/MWh)	12.3413	12.3537	13.0321	13.057	4.1250	4.3908	4.4650
$P(4)$ (\$/MWh)	13.4322	13.6383	15.2445	15.273	4.3428	4.7113	4.7992
$p(5)$ (\$/MWh)	14.1594	14.1887	16.1947	16.215	4.4368	4.8627	4.9657
$P(6)$ (\$/MWh)	13.8032	13.8141	15.5198	15.564	4.3714	4.7535	4.8494
$P(7)$ (\$/MWh)	12.7309	12.7619	14.0169	14.048	4.2224	4.5342	4.6128
$p(8)$ (\$/MWh)	11.8123	11.8236	12.2565	12.265	4.0333	4.2558	4.3260
$p(9)$ (\$/MWh)	11.1089	11.1136	10.9713	10.979	3.9129	4.0917	4.1436
$p(10)$ (\$/MWh)	10.0376	10.0762	9.6156	9.6326	3.7352	3.8959	3.9376
$p(11)$ (\$/MWh)	9.5567	9.6061	9.0539	9.0711	3.6550	3.8075	3.8473
$p(12)$ (\$/MWh)	10.0498	10.0472	9.3001	9.5926	3.7295	3.8896	3.9312
$P(13)$ (\$/MWh)	10.3470	10.379	9.7934	9.9934	3.7868	3.9528	3.9957
$p(14)$ (\$/MWh)	10.8476	10.8584	10.6004	10.613	3.8728	4.0475	4.0922
$P(15)$ (\$/MWh)	11.6503	11.6558	11.9501	11.959	4.0046	4.2137	4.2824
$p(16)$ (\$/MWh)	12.4309	12.4618	13.1966	13.232	4.1422	4.4161	4.4911
$p(17)$ (\$/MWh)	12.9109	12.9322	14.0213	14.048	4.2224	4.5342	4.6128
$p(18)$ (\$/MWh)	12.7244	12.7639	13.7166	13.756	4.1938	4.4920	4.5691
$P(19)$ (\$/MWh)	12.5634	12.5962	13.4402	13.465	4.1651	4.4499	4.5261
$p(20)$ (\$/MWh)	12.2308	12.227	12.9904	12.707	4.1020	4.3571	4.4301
$P(21)$ (\$/MWh)	11.5104	11.5278	11.7746	11.714	3.9817	4.1799	4.2475
$P(22)$ (\$/MWh)	10.7243	10.7448	10.4540	10.474	3.8556	4.0286	4.0730
$p(23)$ (\$/MWh)	10.1002	10.0711	9.3527	9.6581	3.7352	3.8959	3.9376
$p(24)$ (\$/MWh)	9.0768	9.0688	8.4142	8.4302	3.5633	3.7058	3.7442
$\pi_1(10^{\wedge 3}\$)$	10.645	10.742	12.706	12.772	4.5812	4.8959	4.9103
$\pi_2(10^{\wedge 3}\$)$	9.4082	9.427	10.347	10.397	1.7842	2.1386	2.1497
$\pi_3(10^{\wedge 3}\$)$	6.7980	6.822	7.3950	7.427	0.8669	1.0069	1.0469
$\pi_4(10^{\wedge 3}\$)$	7.5781	7.609	6.8590	6.800	0.3997	0.5677	0.6223
$\pi_5(10^{\wedge 3}\$)$	6.5070	6.524	5.7240	5.762	0.2495	0.3769	0.3435
$\pi_6(10^{\wedge 3}\$)$	6.5394	6.545	6.8300	6.854	0.2495	0.3769	0.4157

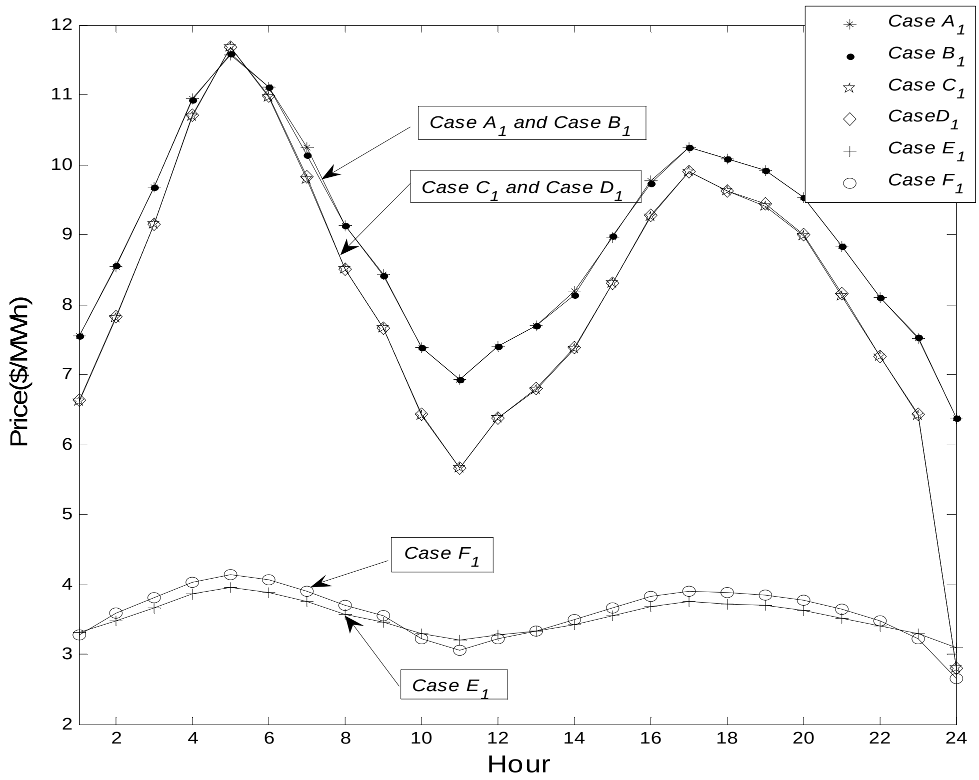

Figure 4.2: Market price of lower demand cases

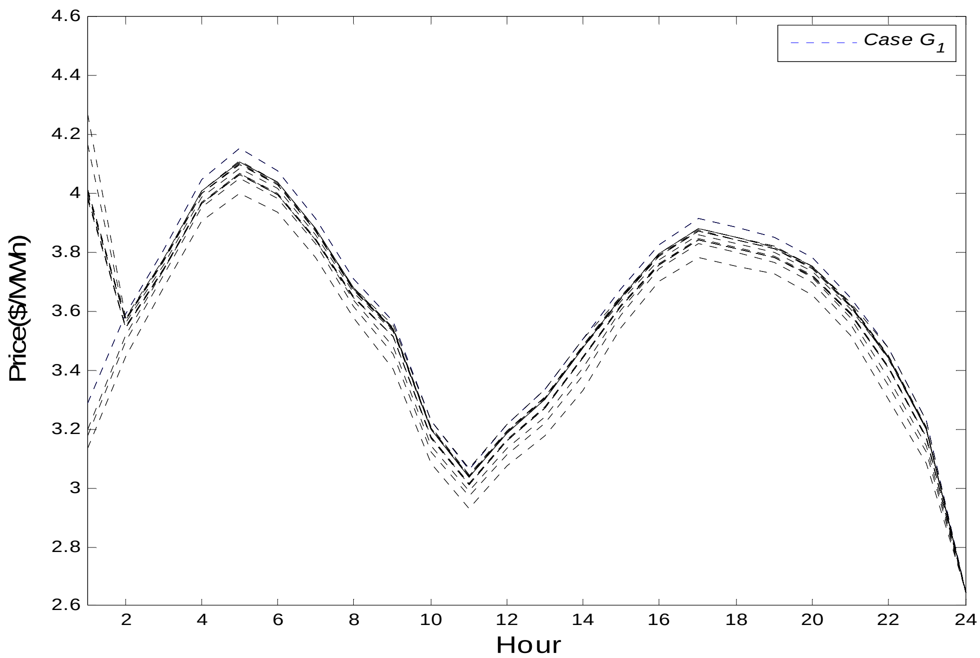

Figure 4.3: Market price of lower demand case with inter-temporal constraints

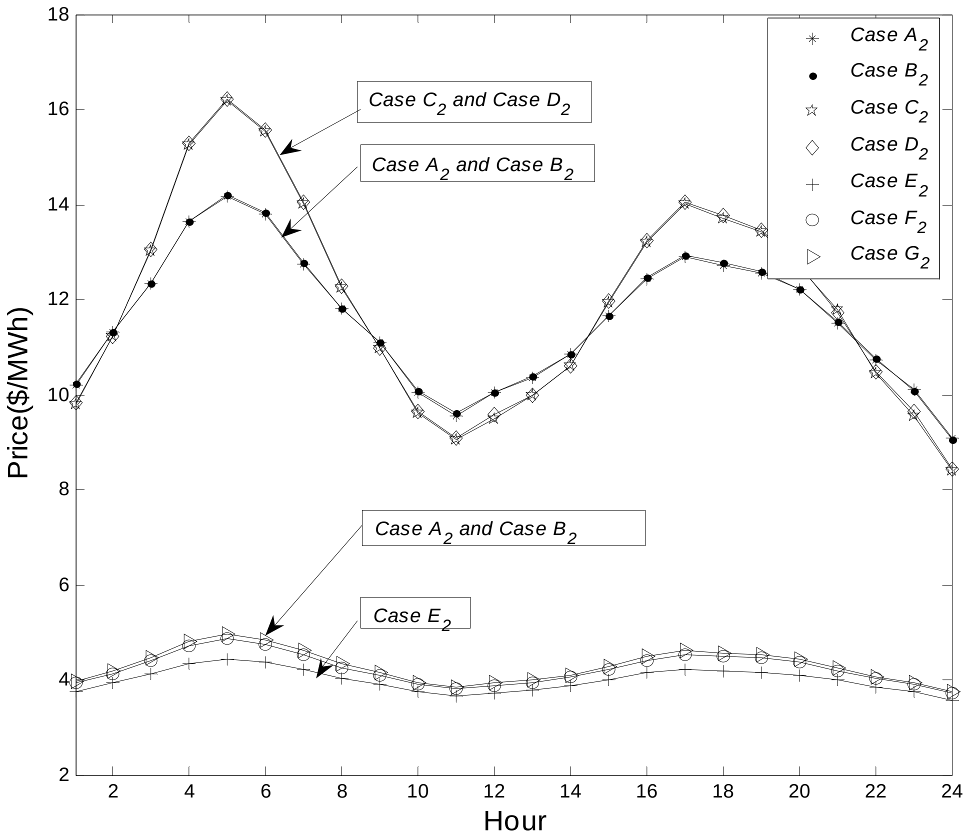

Figure 4.4: Market price of higher demand cases

4.5 Conclusion

A co-evolutionary computation approach has been applied to analyze market equilibrium in multiple pricing period electricity market in this chapter. The capacity constraints and inter-temporal constraints are considered in the market model. It is found that when ISO compels the GenCos with a supply function being constant across multiple pricing period, the market price will be lower than that of Cournot price emerging in a single pricing period market and the market power can also be alleviated. Besides, it is important to further study the outcomes of different markets in which the

GenCos are compelled to bid consistent or not for multiple pricing period. It is also important to observe outcomes and to set up an obligation for consistent bids or not.

CHAPTER 5 ANALYZING TWO-SETTLEMENT ELECTRICITY MARKET EQUILIBRIUM

5.1 Introduction

Due to California electricity crisis, more and more researchers are convinced that the forward contract plays an important role for market power mitigation [3] or risk management [104] in electricity markets. Generally, there are at least three main reasons for the GenCos to enter a forward market: 1) being compelled by regulators as part of a transitional vesting process, which is the situation in many countries, such as England and Wales, Australia and New Zealand; 2) recognizing the importance and necessity of risk management with contractual arrangements [104]; and 3) being encouraged economically [105, 106].

The electricity spot markets modeled by SFE and Cournot models have been extended to include contract markets in [23, 27, 45, 52, 107-109]. The English electricity market is modeled by SFE model with a contract market, and the entry condition of the contract market is discussed in [107]. Reference [27] has showed that competition in contract market could lead the generators to sell contracts and increase their outputs and also hedge the spot market price in England and Wales. Reference [108] proposes an asymmetric LSFE model to develop firms' optimal bidding strategies given their forward contracts. Market power mitigation effects of forward contracts have also been evaluated. Reference [109] examines the issue of whether generators would voluntarily enter contract markets through an economic incentive by a two-stage game model proposed in [105]. The contract market is modeled with the general conjectural variation method. The factors which could affect this strategic contracting behavior are investigated. The dynamics in two-settlement electricity markets are studied by an agent-based model. Numerical simulations illustrate that the access to the forward market leads to more competitive behaviors of the suppliers in the spot market, and thus lower spot energy prices [45]. References [23, 52], determination of the equilibrium in two-settlement electricity markets is formulated as an EPEC using Cournot model, in which each firm solves a MPEC. It is shown that spot market prices will decreases when the supplies enter forward contracts.

The main objective of this chapter is to investigate the issue of whether generators would voluntarily enter the contract market solely through the economic incentive and to examine the factors that could affect the strategic contracting behavior. Therefore, market equilibrium models are required to simulate the competition of generators in spot and forward markets. However, determination of the market equilibrium will be difficult when the forward market and generation capacity constraints are considered. Co-evolutionary computation is successfully used to determine the equilibrium of noncooperative game and market simulation. It can handle the nonlinear market models that are difficult to be handled by conventional methods. Thus, this chapter will employ the co-evolutionary computation to study bidding behavior of the GenCos in a two-settlement market. The impact of forward contracts on market outcomes is then analyzed. The entry condition of GenCos in forward markets and the factors which could affect the bidding behavior are also studied.

5.2 Market Model Formulation

The real electricity market is a multi-settlement market where forward transactions, day-ahead transactions, and real-time balancing transactions are settled sequentially at different prices. It can be simplified as a two-settlement market including a forward market and a spot market. This chapter uses the two-stage game model in [105] to formulate the two-settlement market consisting of a forward market and a spot market. In the first stage, GenCos enter the forward market, forming rational expectations regarding the forward contracts of their rivals and the spot equilibrium outcomes. In the second stage, the GenCos compete in the spot market taking into account all GenCos' forward contracts. The Cournot or LSFE models are used to represent competitive bidding in the spot market, while the forward market is represented by the Cournot model.

5.2.1 Market assumptions

Suppose there are I GenCos (suppliers) in the electricity market. And these GenCos are risk neutral. Each GenCo has a generator and is characterized by the following quadratic cost function:

$$\begin{aligned} & C_i = \frac{1}{2} a_i P_{Gi}{}^2 + b_i P_{Gi} \quad i = 1, \ldots, I \\ & a_i > 0 \end{aligned} \tag{5.1}$$

where P_{Gi} is the quantity generated by Generator *i*; a_i and b_i are the coefficients of the Generator *i*'s cost function. The marginal cost function of Generator *i* is affine as follows:

$$MC_i = \frac{dC_i}{dP_{Gi}} = a_i P_{Gi} + b_i \quad i = 1, \ldots, I \tag{5.2}$$

When there is negligible transmission loss, the aggregate demand P_S, which is assumed to be an inverse linear demand function, will be equal to the total output of all GenCos as shown below:

$$P_S = \overline{P_S} - rp = \sum_{i=1}^{I} P_{Gi} \quad i = 1, \ldots, I \tag{5.3}$$

where p is the spot market price; *r* and $\overline{P_S}$ are coefficients of the demand function. And *r* is the slope of the demand function.

The GenCos compete with each other in the forward market by choosing the quantity of their contracts P_{Gi}^c ($P_{Gi}^c \geq 0$), which they are willing to sell at the forward market price p_i^c. It is assumed that the forward contracts are observable for all the GenCos in spot market. Also the GenCos are assumed to use their bidding strategies, such as quantities of generator in Cournot model and coefficients of supply functions in LSFE model, to compete in the spot market.

5.2.2 Equilibrium model for strategic bidding in the spot market

The GenCos bid in the spot market by using the information observed in the forward market. LSFE model and the less competitive market model, Cournot model, are employed to model the spot market respectively in this section.

Given the decisions of GenCos in the forward market, the optimization problem faced by each GenCo is how to maximize its expected total profit (π_{Gi}), expressed below.

$$\pi_{Gi} = p(P_{Gi} - P_{Gi}^c) + p_i^c P_{Gi}^c - C_i \tag{5.4}$$

1) Cournot model:

In Cournot model, each GenCo will maximize its own profit in (5.4) by changing its decision variable P_{Gi}. The derivative of GenCo *i*'s profit with respect to its decision variable can be written as:

$$\frac{\partial \pi_{Gi}}{\partial P_{Gi}} = (P_{Gi} - P_{Gi}^c)\frac{\partial p}{\partial P_{Gi}} + p - MC_i \tag{5.5}$$

By setting the derivative of GenCo *i*'s profit in (5.5) as zero and eliminating p using (5.3), the optimal value of P_{Gi} can be obtained by:

$$P_{Gi} = \frac{(\overline{P_S} - \sum_{i=1}^{I} P_{Gi} + P_{Gi}^c - b_i r)}{(1 + a_i r)} = \frac{(rp + P_{Gi}^c - b_i r)}{(1 + a_i r)} \tag{5.6}$$

Then, by eliminating P_{Gi} in (5.6) using (5.3), the spot market price can be determined by:

$$p = \frac{1}{r + \sum_{i=1}^{I} \frac{r}{1 + a_i r}} [\overline{P_S} - \sum_{i=1}^{I} \frac{1}{1 + a_i r} P_{Gi}^c + r \sum_{i=1}^{I} \frac{b_i}{1 + a_i r}] \tag{5.7}$$

2) LSFE model:

The GenCos are assumed to compete in the spot market by submitting their bids in the form of LSF. The supply function is a non-decreasing function of price and takes the form as follows:

$$\begin{aligned} p = \alpha_i P_{Gi} + \beta_i \quad & i = 1, \ldots, I \\ \alpha_i > 0 \quad & \end{aligned} \tag{5.8}$$

where α_i and β_i are the coefficients of LSF.

LSFs with *a*-, *b*-, $(a \propto b)$- and (a,b)-parametrization introduced in chapter 3 are studied in this chapter. The equation (5.9) is used to study (a,b)-parametrization in this chapter.

$$p_n\left(P_{Gin}\right) = k_{Gi}(a_i P_{Gin} + b_i) \quad i = 1,\ldots,I \tag{5.9}$$

In LSFE model, each GenCo will maximize its own profit expressed in (5.4) by changing its decision variables α_i, β_i or k_{Gi} according to its parametrization type. By differentiating (5.4) with respect to p and using (5.3) and (5.8), the derivative of GenCo *i*'s profit with respect to p can be written as:

$$\begin{aligned}\frac{\partial \pi_{Gi}}{\partial p} &= (P_{Gi} - P_{Gi}^c) + p\frac{\partial P_{Gi}}{\partial p} - MC_i \frac{\partial P_{Gi}}{\partial p} \\ &= (P_{Gi} - P_{Gi}^c) + (p - MC_i)\frac{\partial(\overline{P_S} - rp - \sum\limits_{j=1, j\neq i}^{I} \frac{p - \beta_i}{\alpha_i})}{\partial p}\end{aligned} \tag{5.10}$$

By setting the derivative of GenCo *i*'s profit in (5.10) as zero, the optimal value of P_{Gi} can be obtained by:

$$P_{Gi} = P_{Gi}^c + (p - MC_i)(r + \sum_{j=1, j\neq i}^{I} \frac{1}{\alpha_j}) \tag{5.11}$$

5.2.3 Equilibrium model for strategic contracting in the forward market

The equilibrium for the forward market can be determined by maximizing GenCos' profits with nesting the equilibrium conditions from the spot market in the calculation. In the forward market, all GenCos are supposed to be able to offer forward contracts. It is also assumed that there are enough risk neutral arbitrageurs in the markets and they will eliminate any profitable arbitrage opportunity arising from the difference between the forward prices and the expected spot prices. Then p_i^c is an unbiased estimator of p [105].

Each GenCo chooses its forward market output so as to maximize its profit, which can be formulated as follows:

$$Max \quad \pi_{Gi} = p(P_{Gi} - P_{Gi}^c) + p_i^c P_{Gi}^c - C_i \tag{5.12}$$

$$s.t. \quad p_i^c = p \quad i = 1, \ldots, I$$

Since the spot price p is an implicit function of the forward market output P_{Gi}^c, the GenCo i's marginal benefit for forward contract is equal to the derivative of its profit with respect to P_{Gi}^c as follows:

$$\frac{\partial \pi_{Gi}}{\partial P_{Gi}^c} = \frac{\partial p}{\partial P_{Gi}^c} P_{Gi} + (p - MC_i) \frac{\partial P_{Gi}}{\partial P_{Gi}^c} \tag{5.13}$$

A Modeling spot market by Cournot model:

Substituting (6) into (13) yields:

$$\frac{\partial \pi_{Gi}}{\partial P_{Gi}^c} = \frac{\partial p}{\partial P_{Gi}^c} P_{Gi} + (p - MC_i)(\frac{r}{1 + a_i r} \frac{\partial p}{\partial P_{Gi}^c} + \frac{1}{1 + a_i r}) \tag{5.14}$$

Then, setting the marginal benefit in (5.14) to zero and using (5.7), the GenCo i's output in the spot market can be obtained as follows:

$$P_{Gi} = (p - MC_i)(r + \sum_{j=1, j \neq i}^{I} \frac{r}{1 + a_j r}) \tag{5.15}$$

By eliminating p in (5.15) using (5.6), the GenCo i's output in forward market can be written as:

$$P_{Gi}^{c} = \frac{\sum_{j=1, j\neq i}^{I} \frac{1}{1+a_j r}}{1+\sum_{j=1, j\neq i}^{I} \frac{1}{1+a_j r}} P_{Gi} \tag{5.16}$$

The fraction of power sold at the forward market in (5.16) and spot market in (5.15) for each GenCo can be determined by:

$$\frac{P_{Gi}^{c}}{P_{Gi}} = \frac{\sum_{j=1, j\neq i}^{I} \frac{1}{1+a_j r}}{1+\sum_{j=1, j\neq i}^{I} \frac{1}{1+a_j r}} = 1 - \frac{1}{1+\sum_{j=1, j\neq i}^{I} \frac{1}{1+a_j r}} \tag{5.17}$$

When r is increasing, the demand becomes more elastic. The GenCos will have less incentive to lift up the market price in spot market. They will bid aggressively (low price for large quantities) in spot market and have less incentive to enter forward market. Then the fraction in (5.17) will become smaller.

It can also be observed that the fraction is affected by the slope of GenCos' marginal cost functions. If a_i is larger than $a_{i'}$ (for any i *and* $i' \in 1,..., I$), $\sum_{j=1, j\neq i}^{I} \frac{1}{1+a_j r}$ is larger than $\sum_{j=1, j\neq i'}^{I} \frac{1}{1+a_j r}$. According to (5.17), $\frac{P_{Gi}^{c}}{P_{Gi}} > \frac{P_{Gi'}^{c}}{P_{Gi'}}$ can be obtained. It means that a GenCo with a large slope of marginal cost function will have more incentive to enter the forward market.

B Modeling spot market by LSFE model:

$\frac{\partial P_{Gi}^{c}}{\partial P_{Gi}}$ is obtained by substituting (5.8) into (5.11) and differentiating it with respect to P_{Gi} as follows:

$$\frac{\partial P_{Gi}^{c}}{\partial P_{Gi}} = \frac{\partial [P_{Gi} - [(\alpha_i P_{Gi} + \beta_i) - (a_i P_{Gi} + b_i)] A_i]}{\partial P_{Gi}} = 1 + (a_i - \alpha_i) A_i \tag{5.18}$$

where $A_i = (r + \sum_{j=1, j\neq i}^{I} \frac{1}{\alpha_j}) > 0$.

Substituting (5.3) and (5.8) into (5.11) and differentiating it with respect to p yields:

$$\begin{aligned}\frac{\partial P_{Gi}^c}{\partial p} &= \partial\{(\overline{P_S} - rp - \sum_{j=1, j\neq i}^{I} \frac{p-\beta_i}{\alpha_i}) \\ &\quad -[(\alpha_i - a_i)(\overline{P_S} - rp - \sum_{j=1, j\neq i}^{I} \frac{p-\beta_i}{\alpha_i}) + (\beta_i - b_i)]A_i\}/\partial p \\ &= -[1 + (a_i - \alpha_i)A_i]A_i\end{aligned} \tag{5.19}$$

Substituting (5.18) and (5.19) into (5.13) produces:

$$\begin{aligned}\frac{\partial \pi_{Gi}}{\partial P_{Gi}^c} &= \frac{-1}{[1+((a_i - \alpha_i)A_i]A_i} P_{Gi} + \frac{(p - MC_i)}{1+(a_i - \alpha_i)A_i} \\ &= \frac{-P_{Gi} + (p - MC_i)A_i}{[1+(a_i - \alpha_i)A_i]A_i}\end{aligned} \tag{5.20}$$

By substituting (5.11) to (5.20), the marginal benefit for the forward contract can be obtained by

$$\frac{\partial \pi_{Gi}}{\partial P_{Gi}^c} = \frac{-P_{Gi}^c}{[1+(a_i - \alpha_i)A_i]A_i} \tag{5.21}$$

1) For a, b or $(a \propto b)$-parametrization of LSF:

By substituting (5.2) and (5.8) to (5.11), the generation output in spot market becomes:

$$P_{Gi} - P_{Gi}^c = (p - MC_i)A_i = [(\alpha_i - a_i)P_{Gi} + (\beta_i - b_i)]A_i \tag{5.22}$$

(5.23a) and (5.23b) are obtained by using (5.11), (5.21) and (5.22) when P_{Gi}^c is not equal to or equal to P_{Gi} respectively.

$$\begin{aligned} 1+(a_i-\alpha_i)A_i &= 1+(a_i-\alpha_i)\frac{P_{Gi}-P_{Gi}^c}{(p-MC_i)} \\ &= 1+(a_i-\alpha_i)\frac{P_{Gi}}{(p-MC_i)}+(\alpha_i-a_i)\frac{P_{Gi}^c}{(p-MC_i)} \\ &= \frac{\beta_i-b_i}{(p-MC_i)}+\frac{(\alpha_i-a_i)P_{Gi}^c}{(p-MC_i)} \end{aligned} \tag{5.23a}$$

$$1+(a_i-\alpha_i)A_i = 1 \tag{5.23b}$$

I) For $P_{Gi}^c = 0$ *:*

$\frac{\partial \pi_{Gi}}{\partial P_{Gi}^c} = 0$ can be obtained according to (5.21).

II) For $0 < P_{Gi}^c < P_{Gi}$ *:*

Using (5.21) and LSFE parametrization condition yields:

$$\begin{cases} p > MC_i \\ \alpha_i \ge a_i \\ \beta_i \ge b_i \\ \alpha_i - a_i + \beta_i - b_i > 0 \end{cases} \tag{5.24}$$

$\frac{\partial \pi_{Gi}}{\partial P_{Gi}^c}$ is less than zero according to (5.21), (5.23a) and (5.24).

III) For $P_{Gi}^c = P_{Gi}$ *:*

$\frac{\partial \pi_{Gi}}{\partial P_{Gi}^c}$ is less than zero according to (5.21) and (5.23b).

IV) For $P_{Gi} < P_{Gi}^c$ *:*

Using (5.21) and LSFE parametrization condition yields:

$$\begin{cases} p < MC_i \\ \alpha_i \le a_i \\ \beta_i \le b_i \\ \alpha_i - a_i + \beta_i - b_i < 0 \end{cases} \tag{5.25}$$

$\frac{\partial \pi_{Gi}}{\partial P_{Gi}^c}$ is less than zero according to (5.21), (5.23a) and (5.25).

Under all the above conditions, GenCos will get negative marginal profit when it sells the forward contract so they have no incentive to enter the forward market.

2) For (a,b)-parametrization of LSF:

The GenCo may select a very large positive α_i as the supply function coefficient. Then, $[1+(a_i-\alpha_i)A_i]$ is less than zero and $\frac{\partial \pi_{Gi}}{\partial P_{Gi}^c}$ in (5.21) becomes larger than zero so GenCos have incentive to enter the forward market

It is found that when GenCos decide their bidding variables using a, b and $(a \propto b)$-parametrization of LSF, the spot market is more competitive. GenCos bid aggressively in spot market and have no incentive to enter forward market because their marginal benefits for forward contracts in the forward market are not larger than zero. However, GenCos may have incentive to enter forward market if they decide their supply functions using (a,b)-parametrization of LSF.

Determination of the market equilibrium in the two-stage game is a difficult task especially for the cases of the spot market under LSFE type competition or GenCos with tight capacity constraints. Therefore, a co-evolutionary computation approach is applied to solve this problem.

5.3 Co-evolutionary Computation Approach to Analyzing Market Model

In this chapter, CGA implemented using real-coded GAs is employed to determine the market equilibrium. The crossover and mutation operators of real-coded GA are described in Chapter 4. GenCos in the forward market and in spot market are represented by species in the outer loop and inner loop respectively in the CGA. So totally 2*I species are needed. To determine the equilibrium of the two-stage game, the backward induction method [84] is merged into the CGA. It proceeds by considering the decisions might be made in spot market by GenCos by fixing forward contracts. Using the information obtained in spot market, GenCos can optimize their strategies in the forward market. Thus to solve the equilibrium of the forward market, the equilibrium of the spot market (i.e. subgame perfect equilibrium [84]) should be determined firstly.

The procedures can be summarized as follows:

Step 1: Set the basic parameters of CGA including crossover rate, mutation rate, maximum generation number and population size in the outer loop and inner loop respectively.

Step 2: The individual of each species, which includes the bidding variable of the GenCo in outer and inner loops, is initialized. All the initial representatives of each species are set randomly.

Step 3: The real-coded GA is applied to solve the optimization problem of each GenCo for the forward market in (5.12). For each individual of the species in the outer loop, a fitness value is assigned according to its profit in (5.12). To get the fitness value, the forward market price, which is equal to the spot market price, is needed so the equilibrium of spot market and the corresponding price are determined first.

Step 3.1: The representatives in the outer loop (i.e. forward contracts of GenCos) are fixed and sent to the inner loop.

Step 3.2: The profit of each GenCo for the spot market in (5.4) is maximized by the real-coded GA with consideration of its generation capacity constraint and system energy balance in (5.3). The corresponding bidding strategy (i.e. the best individual) is then determined. In the optimization, each individual of a species in the inner loop (i.e. a strategy of a GenCo in spot market) is evaluated and assigned a fitness value according to the corresponding profit in (5.4). The market price and total output of the GenCo in (5.4) can be obtained by (5.3) for Cournot model or (5.3) and (5.8) for LSFE model based on representatives of other species in the inner loop (i.e. strategies of other GenCos in spot market). The best individual of each species is the one with the highest fitness value.

Step 3.3: The best individual of each species is selected as the representative in the inner loop and sent to other GenCos.

Step 3.4: Repeat Steps 3.2 and 3.3 using the updated representatives and keeping the best strategy of each GenCo in the population (i.e. elitism) until the maximum generation number in the inner loop is reached.

Step 4: The best individual of each species is selected as the representative of the species in the outer loop and sent to other GenCos.

Step 5: Repeat Steps 3 and 4 using the updated representatives and keeping the best strategy of each GenCo in the population (i.e. elitism) until the maximum generation number is reached in the outer loop.

5.4 Case Study

In this section, a three GenCo test system in [109] and a five GenCo test system in [30] are used to validate the models and theoretical analyses in Section 5.2 and the effectiveness of the CGA in determination of market equilibrium described in Section 5.3. The CGA parameters are given in Table 5.1.

Table 5.1: CGA parameters

Parameters	Description
Variable code type	Real code
Initial population	Randomly initialized population
Population size of outer loop	40
Max. generation of outer loop	200
Population size of inner loop	40
Max. Max. generation of inner loop	40
Mutation	Non-uniform mutation (mutation probability = 0.05, δ = 1)
Crossover	Blend crossover (crossover probability = 0.9)
Selection	Tournament selection size is 2 and 5% population are elitism

5.4.1 Three GenCos study case

The cost parameters of three GenCos in [109] are listed in Table 5.2. The aggregate demand parameters in (5.3) are $\overline{P_S(t)}$ =45GWh and r=0.5GWh/($/MWh).

Table 5.2: Cost coefficients of the three GenCos

GenCo No.	1	2	3
Cost parameter a_i $/(MWh.GWh)	1.0	1.5	2.0
Cost parameter b_i $/MWh	12.0	10.0	8.0

The following simulation cases with and without forward contracts are carried out:

Case A_1: Perfect competition in the spot market without forward market arrangement.

Case A_{21}: Cournot type competition in the spot market without forward market arrangement.

Case A_{22}: LSFE with a-parametrization type competition in the spot market without forward market arrangement.

Case A_{23}: LSFE with b-parametrization type competition in the spot market without forward market arrangement.

Case A_{24}: LSFE with $(a \propto b)$-parametrization type competition in the spot market without forward market arrangement.

Case A_{25}: LSFE with (a, b)-parametrization type competition in the spot market without forward market arrangement.

Case A_{31}: Cournot type competition in the spot market with forward market arrangement.

Case A_{32}: LSFE with a-parametrization type competition in the spot market with forward market arrangement.

Case A_{33}: LSFE with b-parametrization type competition in the spot market with forward market arrangement.

Case A_{34}: LSFE with $(a \propto b)$-parametrization type competition in the spot market with forward market arrangement.

Case A_{35}: LSFE with (a, b)-parametrization type competition in the spot market with forward market arrangement.

Simulation results are shown in Table 5.3. In Case A_{31}, the GenCos have the incentive to enter the forward market when the GenCos use the Cournot type competition in the spot market. The solution of this simple case can be also obtained by solving (5.3), (5.7) and (5.15) using the symbolic tool in Matlab software [110].

By comparing Case A_{31} with Case A_{21}, it can be observed that GenCos prefer not to enter the forward market because they can get more profit without participating in the forward market. However, if one GenCo enters to the forward market, it could benefit from the forward market by producing more output. Other GenCos are prompted to enter the forward market by economic incentive. Finally, as shown in the market equilibrium of Case A_{31}, all GenCos enter the forward market, but they get less profit compared with the case of without participating in the forward market (i.e. Case A_{21}). The prisoners' dilemma-type outcome [105] appears in this situation.

In Case A_{35}, GenCos use LSFE with (a,b)-parametrization in the spot market, the slope and intercept of supply function of each GenCo are not unique, but the market-clearing price and the suppliers' outputs are unique and equal to the results of the Cournot model in Case A_{31}. In this situation, the slope of the supply function is a very large positive value and the intercept is a very large negative value. The GenCos become less competitive and behave like Cournot quantity decision-makers. The simulation result has demonstrated that a focal equilibrium [34] is converged.

When comparing Cases A_{35} and A_{31} with Cases A_{25} and A_{21} respectively, it is clear that the market price is lower and generation output increases when GenCos enter the forward market. The market becomes more competitive, and the market power is mitigated.

Table 5.3: Simulation results for three GenCos example

Case	Gen No.	α_i/a_i or β_i/b_i or k_{Gi}	P_{Gi}^c (GWh)	p ($/MWh)	P_{Gi} (GWh)	π_{Gi} ($10^{\wedge 3}$$)
A_1	1	--	--	25.38	13.38	89.45
	2	--	--		10.25	78.80
	3	--	--		8.69	75.47
A_{21}	1	--	--	39.34	9.11	207.62
	2	--	--		8.38	193.24
	3	--	--		7.83	184.15
A_{22}	1	1.7501	--	31.21	10.97	150.55
	2	1.4604	--		9.68	135.00
	3	1.3272	--		8.74	126.44
A_{23}	1	1.5596	--	29.91	11.19	137.79
	2	1.4977	--		9.95	123.85
	3	1.5135	--		8.90	115.77
A_{24}	1	1.3286	--	30.61	11.04	144.46
	2	1.2375	--		9.82	130.05
	3	1.1921	--		8.84	121.68
A_{25}	1	--	--	39.34	9.11	207.62
	2	--	--		8.38	193.24
	3	--	--		7.83	184.15
A_{31}	1	--	5.48	32.82	10.59	164.45
	2	--	5.07		9.42	148.41
	3	--	4.75		8.58	139.33
A_{32}	1	1.7501	0	31.21	10.97	150.55
	2	1.4604	0		9.68	135.00
	3	1.3272	0		8.74	126.44
A_{33}	1	1.5596	0	29.91	11.19	137.79
	2	1.4977	0		9.95	123.85
	3	1.5135	0		8.90	115.77
A_{34}	1	1.3286	0	30.61	11.04	144.46
	2	1.2375	0		9.82	130.05
	3	1.1921	0		8.84	121.68
A_{35}	1	--	5.48	32.82	10.59	164.45
	2	--	5.07		9.42	148.41
	3	--	4.75		8.58	139.33

The simulation results in Cases A_{32}, A_{33} and A_{34} are the same as that in Cases A_{22}, A_{23} and A_{24} because the GenCos have no incentive to enter the forward market and no forward contract is arranged. It is consistent with the theoretical analysis in Section 5.2.

However, the spot market is still more competitive than that with forward contract arrangement in Cases A_{31} and A_{35}. It can be illustrated that the type of competitions and the parametrizations of LSF affect the GenCos' decisions and market equilibrium significantly.

The effects of the slope of the demand function on the bidding behavior are also studied and the simulation results are shown in Table 5.4. Cases B_1 and B_2 are same as Case A_{31} except for r=0.25 and r=1 respectively. It can be observed in Table 5.4 that the fraction of power sold at the forward market of each GenCo becomes smaller when r increases. Since the system demand is more elastic, the market is more competitive and the spot price reduces. The GenCos prefer to pursuit more profit in the spot market and reduce their output at the forward market. Similar situation can be obtained for Case A_{35}.

Table 5.4: Simulation results for three GenCos example with different slopes of the demand function

Case	Gen. No.	r GWh/ ($/MWh)	P_{Gi}^c (GWh)	p ($/MWh)	P_{Gi} (GWh)	P_{Gi}^c / P_{Gi}	π_{Gi} (10^3$)
B_1	1	0.25	7.17	44.88	12.31	0.5825	329.03
	2		6.64		11.17	0.5944	296.11
	3		6.22		10.29	0.6045	273.70
A_{31}	1	0.50	5.48	32.82	10.59	0.5175	164.45
	2		5.07		9.42	0.5382	148.41
	3		4.75		8.58	0.5536	139.33
B_2	1	1.00	3.24	24.08	7.66	0.4230	63.24
	2		3.13		6.89	0.4543	61.42
	3		3.02		6.37	0.4741	61.87

To investigate the effects of cost parameters on the bidding behavior, the following two cases are performed:

Cases C_1 and C_2 are same as Case A_{31} except for $a_1 = 2$ and $b_1=8$ respectively.

The simulation results are shown in Table 5.5. In Case C_1, $a_1=a_3$, the fraction of GenCo 1 is the same as that of GenCo 3. And in Case C_2, $b_1=b_3<b_2$ and $a_1<a_2<a_3$, the fraction of GenCo 1 is smaller than that of GenCo 2 which is smaller than that of GenCo 3. It is not affected by the intercept of GenCos' marginal cost functions by comparing Case C_2 and Case A_{31}. It is observed that the fraction of power sold at the forward market is only affected by the slope of GenCos' marginal cost functions from Case C_1 and C_2.

Table 5.5: Simulation results for three GenCos example with different cost coefficients

Case	Gen. No.	P_{Gi}^c (GWh)	p (\$/MWh)	P_{Gi} (GWh)	P_{Gi}^c / P_{Gi}	π_{Gi} (10^3\$)
A_{31}	1	5.48	32.82	10.59	0.5174	164.45
	2	5.07		9.42	0.5385	148.41
	3	4.75		8.58	0.5532	139.33
C_1	1	4.08	35.41	7.89	0.5172	122.44
	2	5.08		10.16	0.5000	180.73
	3	4.78		9.24	0.5172	167.87
C_2	1	6.23	31.67	12.04	0.5174	212.53
	2	4.82		8.94	0.5385	133.81
	3	4.53		8.18	0.5532	126.70

The effects of capacity constraints on the bidding behavior are studied and the simulation results are shown in Table 5.6. Cases D_1, D_2, D_3, D_4 and D_5 are same as Cases A_{31}, A_{32}, A_{33}, A_{34} and A_{35} except for $\overline{P_{G1}} = 5$GWh. It can be observed that the market price will become higher when the capacity constraint is hit by comparing the simulation results of Cases D_1, D_2, D_3, D_4 and D_5 in Table 5.6 with that of Cases A_{31}, A_{32}, A_{33}, A_{34} and A_{35} in Table 5.3 respectively. When GenCo 1 hits its capacity constraint, it could not increase its output to change the market price (p) and to pursuit more profit. Then its expected profit in forward market defined in (5.12) (i.e. $p\overline{P_{G1}} - C_1(\overline{P_{G1}})$) is not affected by its forward contract output. The total output of GenCo 1 is unique and same as its maximum output of generation, but its output in the forward market is not unique as shown in Cases D_1, D_2, D_3, D_4 and D_5.

Table 5.6: Simulation results for three GenCos example with capacity constraints

Case	Gen. No.	α_i/a_i or β_i/b_i or k_{Gi}	P^c_{Gi} (GWh)	p ($/MWh)	P_{Gi} (GWh)	π_{Gi} ($10^{3}$$)
D_1	1	--	*	39.68	5.00	125.92
	2	--	3.49		10.48	228.67
	3	--	3.52		9.68	213.01
D_2	1	*	*	39.02	5.00	122.59
	2	1.8159	0		10.65	224.03
	3	1.5766	0		9.84	208.36
D_3	1	*	*	37.44	5.00	114.70
	2	2.0976	0		10.98	210.83
	3	2.1040	0		10.30	197.18
D_4	1	*	*	38.52	5.00	120.13
	2	1.4762	0		10.73	219.75
	3	1.3754	0		10.01	205.31
D_5	1	--	*	39.68	5.00	125.92
	2	--	3.49		10.48	228.67
	3	--	3.52		9.68	213.01

'*' means the solution is not unique.

5.4.2 Five GenCos study case

A more realistic five GenCos test system in [30] is used to further validate the previous analysis. The test system is based on the cost data for the five strategic firms in England and Wales subsequent to the 1999 divestiture. The cost parameters of five GenCos are listed in Table 5.7. The aggregate demand parameters in (5.3) are $\overline{P_S(t)}$ =35GWh and r=0.1GWh/(£/MWh).

Table 5.7: Cost coefficients of the five GenCos

GenCo No.	1	2	3	4	5
Cost parameter a_i ￡/(MWh.GWh)	2.687	4.615	1.789	1.930	4.615
Cost parameter b_i ￡/MWh	12	12	8	8	12

Table 5.8: Simulation results for five GenCos example

Case	Gen No.	α_i/a_i or β_i/b_i or k_{Gi}	P_{Gi}^{c} (GWh)	p (￡/MWh)	P_{Gi} (GWh)	π_{Gi} (10^3￡)
E_1	1	--	--	26.87	5.54	41.17
	2	--	--		3.22	23.97
	3	--	--		10.55	99.57
	4	--	--		9.78	92.30
	5	--	--		3.22	23.97
E_{21}	1	--	--	80.40	5.39	329.66
	2	--	--		4.68	269.57
	3	--	--		6.14	410.86
	4	--	--		6.07	403.80
	5	--	--		4.68	269.56
E_{22}	1	1.3106	--	32.85	5.92	76.32
	2	1.1672	--		3.87	46.11
	3	1.5035	--		9.24	153.18
	4	1.4597	--		8.82	144.06
	5	1.1671	--		3.87	46.11
E_{23}	1	1.3051	--	31.50	5.90	68.27
	2	1.1776	--		3.76	40.71
	3	1.8282	--		9.43	142.09
	4	1.7677	--		8.99	133.31
	5	1.1776	--		3.76	40.71
E_{24}	1	1.1594	--	32.30	5.90	73.01
	2	1.0889	--		3.83	43.89
	3	1.3090	--		9.32	148.79
	4	1.2836	--		8.89	139.78
	5	1.0889	--		3.83	43.89
E_{25}	1	--	--	80.40	5.39	329.68
	2	--	--		4.68	269.54
	3	--	--		6.14	410.85
	4	--	--		6.07	403.79
	5	--	--		4.68	269.54
E_{31}	1	--	4.50	42.80	5.98	136.09
	2	--	3.33		4.39	90.71
	3	--	6.08		8.11	223.34

	4	--	5.90		7.86	213.92
	5	--	3.33		4.39	90.71
	1	1.3106	0		5.92	76.31
	2	1.1670	0		3.87	46.11
E_{32}	3	1.5033	0	32.85	9.24	153.17
	4	1.4597	0		8.82	144.05
	5	1.1672	0		3.87	46.10
	1	1.3050	0		5.90	68.27
	2	1.1776	0		3.76	40.71
E_{33}	3	1.8282	0	31.50	9.43	142.09
	4	1.7677	0		8.99	133.31
	5	1.1776	0		3.76	40.71
	1	1.1595	0		5.90	73.01
	2	1.0889	0		3.83	43.89
E_{34}	3	1.3090	0	32.30	9.32	148.79
	4	1.2837	0		8.89	139.78
	5	1.0890	0		3.83	43.89
	1	--	4.50		5.98	136.09
	2	--	3.33		4.39	90.71
E_{35}	3	--	6.08	42.80	8.11	223.34
	4	--	5.90		7.86	213.92
	5	--	3.33		4.39	90.71

Different simulation cases without and with forward contracts are carried out and the results are shown in Table 5.8. In this study, Cases E_1, E_2, E_{31}, E_{32}, E_{33}, E_{34}, E_{41}, E_{42}, E_{43}, E_{44} and E_5 are same as Cases A_1, A_2, A_{31}, A_{32}, A_{33}, A_{34}, A_{41}, A_{42}, A_{43}, A_{44} and A_5 in three GenCos example respectively.

It can be observed that the simulation results of this five GenCos system are consistent with that of the three GenCos system. The prisoners' dilemma-type outcome appears in Case E_{31} and a focal equilibrium is converged in Case E_{35}. In Cases E_{32}, E_{33} and E_{34}, the GenCos have no incentive to enter the forward market. When comparing Case E_{35} and E_{31} with Case E_{25} and E_{21} respectively, it is also found that the forward market with Cournot type competition or LSFE type competition with

(a, b)-parametrization can make the market more competitive and mitigate the market power.

5.5 Conclusion

A two-stage game model has been presented to model the two-settlement electricity market and to investigate whether a GenCo would enter forward market due to economic inspiration and which factors could affect their strategic behaviors. A co-evolutionary approach has been introduced and successfully employed to determine the market equilibrium of the two-stage game model in two numerical examples. Simulation results show that whether GenCos would enter the forward market depends significantly on what type of competitions in the spot market and whether generation capacity constraints are hit. When the forward market is under Cournot type competition or LSFE type competition with (a, b)-parametrization, GenCos may enter the forward market due to the economic incentive and also mitigate the market power. They may also enter forward market when their capacity constraints are hit. It is also found that their levels of participation in forward market depend significantly on the slope of the demand function and the slope of their marginal cost function.

CHAPTER 6 CONCUSION AND FUTURE WORK

6.1 Conclusion

Electricity restructuring has taken place in many countries to create competitive electricity markets. In these electricity markets, participants submit bids to a market pool that determines the market prices and transactions. This analysis of market equilibrium is of fundamental importance because it provides regulators with relevant information to identify and mitigate the exercise of market power. It also provides GenCos with the appropriate information to maximize their respective profits, within the regulatory framework, by altering market clearing prices to their own respective benefits.

The co-evolutionary computation is developed and employed to analyze the market equilibrium. The thesis establishes the mathematical models for single pricing period market, multi pricing period market and two-settlement market; investigates the convergence process of co-evolutionary computation; and uses co-evolutionary computation and game theories to analyze the equilibrium of electricity markets.

Firstly, the parallel CGA has been successfully applied to determine the market equilibrium in electricity market with generation capacity and transmission constraints under the LSFE model and the Cournot model. The simulation results show that the LSFE under (a,b)-parametrization converges to a focal equilibrium which is equal to

Cournot equilibrium under the capacity and transmission constraints in all cases. The simulation results have also shown that the system may not have a pure equilibrium due to the transmission congestion. But an equilibrium continuum may exist when the generation capacity of generators becomes tighter in LSFE under *a*-, *b*- and $(a \propto b)$-parametrization. The solutions of market power analysis are different and depending on the parameters selected in different types of LSFE. It is also demonstrated that when these constraints are hit, the market price will increase and the abuse of market power can become more serious. But tighter constraints lead the solution of LSFE under *a*-, *b*- and $(a \propto b)$-parametrization close to the solution of Cournot model.

Secondly, the parallel CGA has been employed to study market equilibrium in multi-period electricity market. The capacity constraints and inter-temporal constraints are considered in the market model. Simulation shows when ISO compels the market GenCo uses a supply function be constant across multiple pricing period, the market will generate low price than the Cournot price that can emerge in a market where a supply function is specified for a single pricing period. It is important to observe outcomes of market rule to set up an obligation for consistent bids or not.

Finally, a two stage game model is presented to investigate whether a rational GenCo would enter forward market or not only by economic incentive and what factors could affect this strategic behavior. A co-evolutionary approach is successfully employed to determine the market equilibrium in this two stage game model. Two numerical examples have been used to substantiate the theoretical analysis. Simulation results show that whether GenCos would enter the forward market relies heavily on what type competition in the spot market. When the GenCos use Cournot type competition or LSFE type competition with (a,b)-parametrization, they will enter the forward market and mitigate the market power. They also enter forward market when the capacity is hit. Otherwise they would not enter the forward market. The degree to which a GenCo enters to the forward market is also affected by the slope of the demand function and the slope of its marginal cost function.

6.2 Future Work

An emerging issue in market power analysis and market design has been the interaction of pollutant emission permits markets and energy markets. One generator (i.e. thermal unit) only allows emitting a fixed amount of pollutant, and this permit of generator can be traded in secondary markets. To make sure that an affected facility's emissions do not exceed the amount of its emission, the facility can reduce pollution through operational or equipment changes, or purchase permits from other companies who have excess permits. Excess permits can be sold, or banked for future use. If permits are in short supply and there is significant market concentration, it may be possible for large generators to exercise market power in both energy and permits markets. Profit-maximizing strategies might differ for such GenCos when both markets are considered. Then market simulation should also consider total regional or national emissions.

In Chapter 5, a two-stage game model is presented to investigate two-settlement market. One limitation of the model is the assumption of risk neutrality on the GenCos.

Unfortunately, introducing risk aversion will make the objective functions of GenCos non-quadratic which significantly increases the computational complexity of the model. And future works are also needed to investigate the bidding behaviors of GenCos when the risk aversion GenCos exist or the price difference between spot and forward markets (i.e. not perfect arbitrage) are considered. These works are needed to make the simulation results close to real market outcome.

APPENDIX

Appendix A: List of Abbreviation

ACE	Agent-based Computation Economics
ACO	Ant Colony Optimization
BBP	Bid-Based Pool
CCA	Cooperative Co-evolutionary Algorithm
CGA	Co-evolutionary Genetic Algorithm
CV	Conjectural Variation
CVBS	Conjecture Variable Based Bidding Strategy
DC	Direct Current
DE	Differential Evolution
DP	Dynamic Programming
DP-SC	Dynamic Programming-Sequential Combination
EA	Evolutionary Algorithm
ED	Economic Dispatch
EP	Evolutionary Programming
EPEC	Equilibrium Problem with Equilibrium Constraints
ES	Evolutionary Strategies
GA	Genetic Algorithm
GenCo	Generation Company
GTBS	Game Theoretic Bidding Strategies
HHI	Herfindahl–Hirschman Index
ISO	Independent System Operator
LCP	Linear Complementary Program
LI	Lerner Index
LSF	Linear Supply Function
LSFE	Linear Supply Function Equilibrium
MC	Marginal Cost
MPEC	Mathematical Program with Equilibrium Constraints

MO	Market Operator
NE	Nash Equilibrium
NLP	Nonlinear Complementary Program
OPF	Optimal Power Flow
PCMI	Price–Cost Margin Index
PSO	Particle Swarm Optimization
SFE	Supply Function Equilibrium
UC	Unit Commitment

Appendix B: Data for IEEE 30-bus system

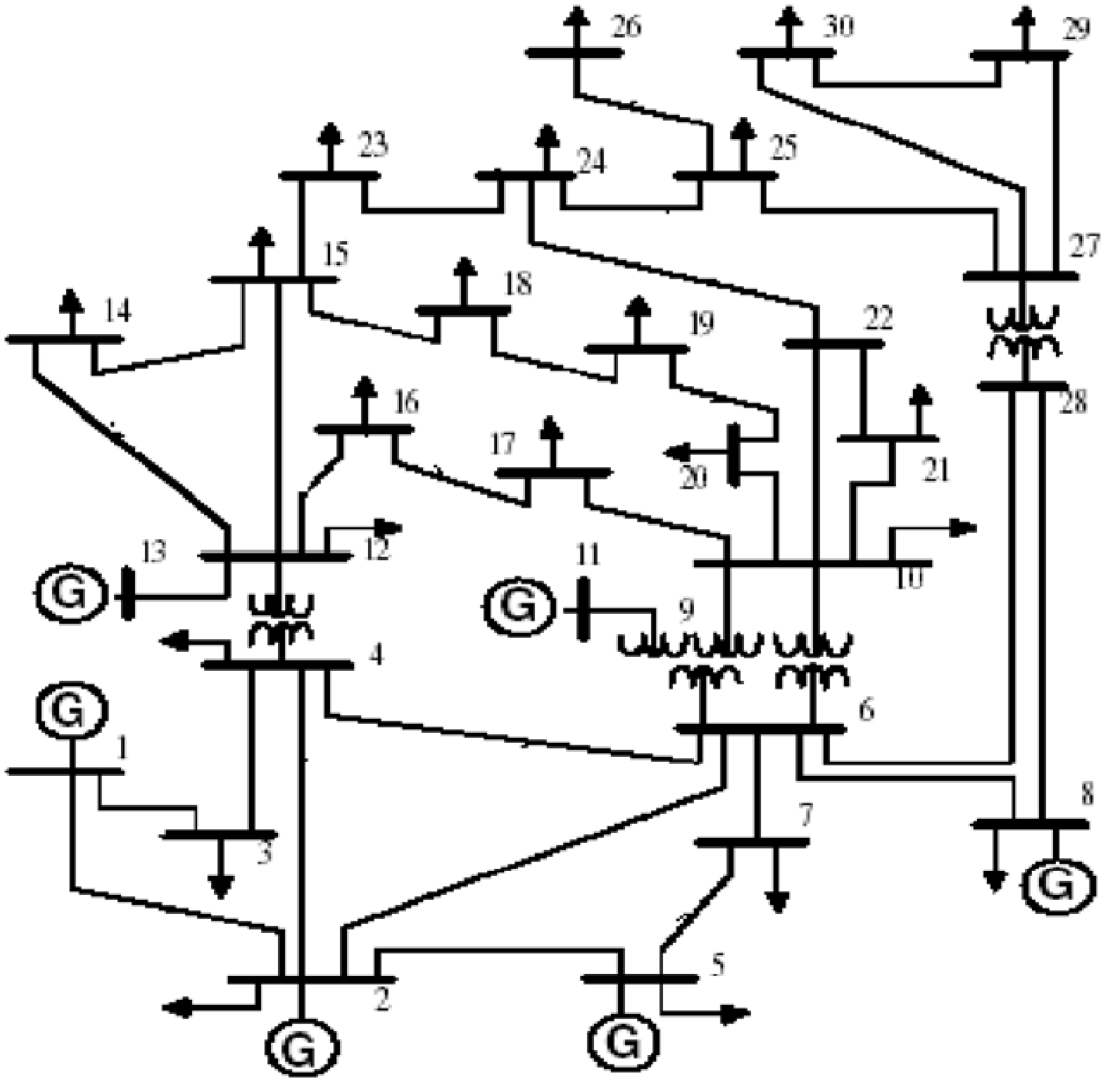

Figure B.1: IEEE 30-bus test system

Table B.1: Coefficients of generators' cost function for IEEE 30-bus system

Generator No.	Bus No.	a_i ($/(MW)^{2}h)	b_i ($/MWh)	c_i ($/h)	$\underline{P_{Gi}}$ (MW)	$\overline{P_{Gi}}$ (MW)
1	1	0.0075	2.0	0	50	200
2	2	0.035	1.75	0	20	80
3	5	0.125	1.0	0	15	50
4	8	0.01668	3.25	0	10	35
5	11	0.05	3.0	0	10	30
6	13	0.05	3.0	0	12	40

Table B.2: Branch data for IEEE 30-bus system

Branch No.	Bus No.	Resistance R(p.u.)	Reactance X(p.u.)	Transmission capacity
1	1-2	0.0192	0.0575	130
2	1-3	0.0452	0.1852	130
3	2-4	0.0570	0.1737	65
4	3-4	0.0132	0.0379	130
5	2-5	0.0472	0.1938	130
6	2-6	0.0581	0.1763	65
7	4-6	0.0119	0.0414	90
8	5-7	0.0460	0.116	70
9	6-7	0.0267	0.082	130
10	6-8	0.0120	0.042	32
11	6-9	0.0000	0.208	65
12	6-10	0.0000	0.556	32
13	9-11	0.0000	0.208	65
14	9-10	0.0000	0.11	65
15	4-12	0.0000	0.256	65
16	12-13	0.0000	0.14	65
17	12-14	0.1231	0.2559	32
18	12-15	0.0662	0.1304	32
19	12-16	0.0945	0.1987	32
20	14-15	0.2210	0.1997	16
21	16-17	0.0824	0.1932	16
22	15-18	0.1070	0.2185	16
23	18-19	0.0639	0.1292	16
24	19-20	0.0340	0.068	32
25	10-20	0.0936	0.209	32
26	10-17	0.0324	0.0845	32
27	10-21	0.0348	0.0749	32
28	10-22	0.0727	0.1499	32
29	21-22	0.0116	0.0236	32
30	15-23	0.1000	0.202	16
31	22-24	0.1150	0.179	16
32	23-24	0.1320	0.27	16
33	24-25	0.1885	0.3292	16
34	25-26	0.2544	0.38	16
35	25-27	0.1093	0.2087	16
36	27-28	0.0000	0.396	65
37	27-29	0.2198	0.4153	16
38	27-30	0.3202	0.6027	16
39	29-30	0.2399	0.4533	16
40	8-28	0.0636	0.2	32
41	6-28	0.0169	0.0599	32

Table B.3: Load data for IEEE 30-bus system

Bus No.	Load(MW)	Bus No.	Load(MW)
1	0	16	3.5
2	21.7	17	9.0
3	2.4	18	3.2
4	7.6	19	9.5
5	94.2	20	2.2
6	0.0	21	17.5
7	22.8	22	0.0
8	30.0	23	3.2
9	0.0	24	8.7
10	5.8	25	0.0
11	0.0	26	3.5
12	11.2	27	0.0
13	0.0	28	0.0
14	6.2	29	2.4
15	8.2	30	10.6

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