STRATEGIC BIDDING FOR LOAD SERVING ENTITY IN ELECTRICITY MARKETS

BY

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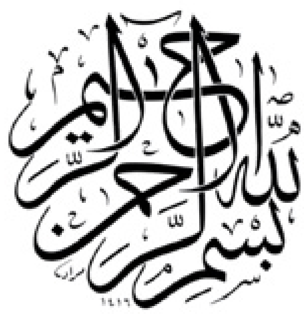

Dedicated to

My Mother, Father

And

My Brother, Sisters

Whose Prayers and Perseverance

led to this accomplishment

ACKNOWLEDGEMENT

In the name of ALLAH, the Most Gracious and the Most Merciful

All praises and glory be to ALLAH (SWT), The Majestic, The Almighty for bestowing me with knowledge, guidance, patience, courage, opportunities abound and showering upon me his mercy and guidance all through the life. I pray that He continues the same the rest of my life. And may peace and blessings of ALLAH be upon Prophet Muhammad, a guidance and inspiration to our lives.

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"SubhanALLAH wAlhamdulillah wa La Ilaha illa ALLAH wALLAHuakbar... La Hawla wala Quwwata Illa Billah"

"How Perfect and Glorified ALLAH is, All Praise is for ALLAH, none has the right to be worshipped except ALLAH, and ALLAH is the greatest... There is no Might nor Power except with ALLAH"

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

THESIS ABSTRACT (ENGLISH)

Name: MOHAMMED AFZAL BIYABANI

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The introduction of competition in electricity markets has allowed the companies to compete freely in the market for the provision of electricity which benefits the consumers and encourage companies to choose different technologies in order to maximize their profit. Absence of Demand Side Participation (DSP) into the market results in price spikes, shortages and market power exercises. This thesis studies the participation of demand side into electricity markets which results in optimal pricing which guarantee some benefits like reducing the total supply-side and demand-side costs of meeting demand during critical periods.

In this thesis, an optimal bidding strategy for Load Serving Entity (LSE) is developed for a pool based double-sided auction electricity market covering two models. The first model neglects the effect of transmission constraints whereas the second model takes into account the impacts of transmission constraints on the profit of LSEs. In this market, sealed auction with pay-as-bid (PAB) settlement and step-wise bidding protocols are used. The bidding behaviors of rivals are represented as stochastic variables of normal probability distributions. The problem is then formulated as a multi-objective stochastic optimization model and solved by a Monte-Carlo Simulation and Genetic Algorithm (GA). A numerical example involving Generation companies (Gencos) and LSEs without transmission constraints (first model) is presented for illustrating the essential feathers of the proposed model and method. The effects of retail prices, interruptible prices, correlation co-efficient, risk factor, single block bidding per unit time and three blocks bidding per unit time are also studied in the research. Finally, the impact of transmission constraints on bidding strategy of LSE is presented using IEEE-30 bus system. The effect of forward contracts on the profit of LSE is also included in the thesis. It has been found that three bidding block per unit time strategy with forward contracts is the best selection for load serving entity.

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THESIS ABSTRACT (ARABIC)

الاســــــــــــم: محمد أفضل بياباني

عنوان الرسالة: إستر اتيجيات المزايدة لشركات خدمات التوزيع في أسواق الكهرباء

التخصـــــــــص: الهندسة الكهربائية

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أدى تنافس شركات تزويد الطاقة الكهربائية في سوق الكهرباء الى فائدة المستهلكين، وشجعها على استخدام تقنيات مختلفة بهدف زيادة الأرباح. ينتج عن غياب مشاركة جانب الطلب في السوق قفزات في الأسعار، عجز، وممارسات سوق الطاقة. تدرس هذه الاطروحة أثر جانب الطلب في سوق الكهرباء والتي تؤدي الى أسعار مثالية، والذي بدوره يضمن بعض الفوائد كتقليل جانب التزويد الكلي، ومقاربة الأسعار في جانب الطلب الى الطلب في الأوقات الحرجة.

تم في هذه الأطروحة تطوير استراتيجية مزاودة مثالية لخدمة الحمولة الكائنة، لصندوق مشترك لمزاد ذو جانبين في سوق الكهرباء والذي يغطي نموذجين. بينما يتجاهل النموذج الأول تأثير شروط النقل، يأخذ النموذج الثاني تأثير شروط النقل على الربح لخدمة الحمولة الكائنة في عين الاعتبار. في هذا السوق،تم استخدام المزاد المغلق حيث الاتفاق وفق الدفع حسب المزايدة، وبروتوكولات مزايدة على مراحل. تم تمثيل سلوك المزايدة للمنافسين بمتغيرات عشوائية تتبع التوزع الطبيعي الإحصائي. ثم تم تشكيل المعضلة وفق نموذج أمثلة عشوائي متعدد الأهداف، وتم حله باستخدام "محاكاة مونتي-كارلو" والخوارزميات الجينية. تم عرض المثال العددي الذي يتضمن Gencos وخدمات الحمولة الكائنة بدون شروط النقل (النموذج الأول) لايضاح الخصائص الأساسية للنموذج والطريقة المقترحة. شمل هذا البحث أيضا على دراسة آثار أسعار البيع المفرق، الأسعار القابلة للمقاطعة، معامل الترابط، عامل الخطر، والمزايدة الأحادية في الوحدة الزمنية. وأخيرا، تم عرض تأثير شروط النقل في استرتيجية المزايدة لخدمة الحمولة الكائنة عرضت باستخدام نظام النقل IEEE-30. كما تم تزويد أثر العقود العاجلة على ربح خدمة الحمولة الكائنة. وقد وجد أن ثلاثة عطاءات في كتلة استراتيجية وحدة زمنية مع العقود الآجلة هي أفضل اختيار لتحميل الكيان خدمة.

درجة الماجستير في العلوم

جامعة الملك فهد للبترول والمعادن

الظهران، المملكة العربية السعودية ديسمبر 2011

CHAPTER 1

INTRODUCTION

1.1 Introduction to Competitive Electricity Markets

During most of twentieth century, consumers used to buy electrical energy from a utility that holds the monopoly for the supply of electricity services in the franchise area. In the 1980s, some economists argued that the monopolistic electric utilities remove the incentive to operate efficiently and encouraged unnecessary investments. The economists suggested that if companies were allowed to compete freely for the provision of electricity that may benefit consumers. Competing companies would choose different technologies in order to maximize their profit and hence the consumers would less likely be saddled with the consequences of unwise investments. Thus the introduction of competition in the supply of electricity has been accompanied by deregulation and hence privatization of some or all components of the industry[1] .

In an open access electricity market, the price of electricity is determined by the Independent System Operator (ISO) or Market Operator (MO) for specific intervals during a specific period considering various economical and operational factors. This results in uncertainty in electrical market price. In 'Fake Markets', generators bid to supply a fixed amount of a power and the market clearing price is set by the marginal price of the most expensive generator scheduled to serve the forecasted load where as demand side does not contribute in the price setting process. When both suppliers and consumers are allowed to operate freely in a competitive market, the intersection of supply and demand curves gives the Market Clearing Price (MCP). The profit obtained from this competition will be then optimal. This type of market is called a “Real Competitive Power Market”. If Demand side participation does not respond to the dynamic wholesale prices, generators would have no incentive to bid closer to their marginal cost in the electricity markets and so prices could not be set closer to the perfectly competitive market price. The absence of Demand Side Participation (DSP) in electricity markets may cause the price spikes, shortages, and exercises of market power[2, 3].

Once the Demand Side participates into the market it forms a Double-Sided competitive electricity market where in suppliers and consumers submit their supply and demand bids in a sealed format to the independent system operator. The ISO then constructs the hourly aggregated supply offers and demand bids and determines the Market Clearing Price (MCP) and correspondingly supply and demand schedules. The winners of the market will be paid (or) pay the MCP for each MW of electric power supplied (or) purchased in the market. The main aim of the Suppliers and Load Serving Entities (LSEs) in the market is to maximize their profit. The LSEs under double-sided competitive electricity market environment are required to compete with the rivals by bidding into the market and hence to a certain extent the profits of LSEs depend on their bidding strategies. Thus, it is important for LSEs to construct an optimal bidding strategy in order to maximize their profit. The main factors which affect the bidding behavior are the demand variation, regulatory constraints; and the bidding behavior of other competitors. Due to special nature of electricity the most uncertain factor is the rivals bidding behavior that compounds the difficulties in bidding decision process where each player tries to maximize their own profits[4].

Now, the challenge is how to develop optimal bidding strategies for LSEs. There have been several approaches which were proposed to build optimal bidding strategy. The first approach is to estimate the Market Clearing Price (MCP) in the next period. The second approach is based on game theory and the third is based on the estimation of bidding behaviors of the rivals participating in the electricity market. Out of these approaches, most of the research to develop optimal bidding strategy is done using the third approach. Here the LSEs make use of the available information about rivals such as historical bidding data and forecasted load data and then estimate the rivals bidding behavior. LSEs face many risks while adopting bidding strategies. If the bidding price is too low then there is a risk of not clearing the quantity required which reduces the profit of selling electric power to end customers. If the bidding price is too high, then there is a risk of paying unnecessary prices for purchasing electricity and end customers may look for another LSEs due to high retail prices[5].

1.2 Thesis Motivation

The main purpose of the research is to study how the Demand Side participation affects the electricity market without and with transmission constraints. Once the Demand side participates into the electricity, what should be the approach to construct an optimal bidding strategy for LSEs so as to maximize its profit which is affected by the rivals bidding behavior and various risk factors? Also how congestion effects on the feasibility of power flow and how should LSEs tackle the problem of congestion? It is necessary to find out how the contractual tools are beneficial to manage risks associated with congestion and whether they affect the benefits of LSEs. All these questions warrant a study about demand side participation and construction of an optimal bidding strategy for LSEs.

An optimal bidding strategy for LSEs is developed for a pool based double-sided auction electricity market with two models. The first model neglects the effect of transmission constraints whereas the second model takes into account the impact of transmission constraints on the profit of LSEs. The bidding behaviors of rivals are represented as stochastic variables of normal probability distributions. The problem is then formulated as a multi-objective stochastic optimization model and solved by a Monte-Carlo Simulation and Genetic Algorithm (GA). A numerical example involving Generation companies (Gencos) and LSEs without transmission constraints is used to illustrate the essential features of the proposed model and method. The impact of transmission constraints on bidding strategy of LSE is studied using IEEE-30 bus system. The thesis also includes the effect of forward contracts on the profit of LSE.

1.3 Thesis Objectives

1. To study different bidding options for Load Serving Entity using single block bidding per unit time with correlation coefficient.
2. To study different bidding options for Load Serving Entity using three blocks bidding per unit time with correlation coefficient.
3. To develop an optimal bidding strategy for LSE with risks in pool-based double-sided competitive electricity.
4. To study the impact of transmission constraints on bidding options for LSE considering single and three block bidding per unit time with correlation coefficient tested on IEEE 30 bus system.

1.4 Thesis Organization

This thesis is organized as follow

In the second chapter of the thesis, a literature survey is presented on the basic concepts of electricity markets. These concepts discuss what the electricity markets consists of and how the electricity markets are run. Different pricing schemes of electricity markets are discussed along with different market clearing processes and settlements. The chapter also presents a literature survey on Demand Side Participation (DSP). This study discusses the importance of DSP within the electricity markets and its effects on the market. Accomplishment of DSP with respect to retailers and consumers perspective is discussed. A literature review on the impact of transmission constraints on the electricity markets is also documented in this chapter. A short discussion about nodal pricing and losses in transmission networks is presented. It also discusses about various techniques used to manage the transmission risks in centralized electricity markets. Finally, the chapter discusses the various approaches of bidding strategies for electricity market participants.

Chapter three presents a mathematical model for optimal strategic bidding for LSEs in double-sided competitive electricity markets is constructed using Y independent Generation Companies (Gencos) and Z independent LSEs. The chapter also documents a literature review on Monte-Carlo Simulation and Genetic Algorithm (GA) methods. Finally, the procedure for building an optimal bidding strategy for an LSE is documented with a flowchart.

Chapter four is divided into two parts. The first part presents the simulation analysis of constructing bidding strategy of a market model consisting of 3 Gencos and 4 LSEs without considering transmission constraints. Various bidding scenarios based on risk factors, correlation co-efficient, retail price to end customers and interruptible price to end customers are analyzed. Monte-Carlo Simulation and Genetic Algorithm (GA) are the two mathematical tools used to determine the optimal bidding strategy for a LSE. The second part presents the simulation analysis of an electricity market model which takes into account the impacts of transmission constraints. The IEEE-30 bus system model is used for the study. The system will be assumed to consist of 6 Gencos and 3 LSEs. At first, an Optimal Power Flow (OPF) is conducted without considering the transmission constraints. Secondly, OPF with transmission constraints is performed and the impact of transmission constraints on the electricity model is studied along with its impact on the profit of concerned LSE. Finally, an optimal bidding strategy for IEEE- 30 bus system model is developed using Monte-Carlo Simulation and GA.

Chapter 5 includes Conclusion and Future Work.

CHAPTER 2

LITERATURE REVIEW

The literature review is divided into the following categories: At first, a survey on the electricity markets and pricing settlements will be discussed and secondly, the role of demand side participation and its importance in electricity markets is documented. The impact of transmission constraints on electricity markets is discussed and the managing of transmission constraints is documented. Finally, a literature survey on the strategic bidding approaches for market participants in an electricity market is presented.

2.1 Introduction

The electricity markets are based on the premise that electricity can be treated as a commodity. However, there are many differences between electricity and other commodities. The basic difference is that electrical energy is connected to a physical system which functions faster than any other market[6]. This physical system consists of generation, transmission, distribution and utilization. The generation and load should always be balanced else it would result in the collapse of the system. Such collapses are not tolerable as it stops not only the trading system but also the entire region goes without power for long periods. The other difference between electricity and other commodity is that the power generated by one generator cannot be specified to a particular consumer. It has to be pooled since ‘the electrical energy produced by different generators is indistinguishable’. This pooling is very economic. The load in the electricity markets varies hourly, daily and weekly. This variation in the load has to be met with time to time[7, 8].

Considering all the factors mentioned above, there is a need of an electricity market where in sellers and buyers interact without any interruption. Buyers and sellers interact based on the equilibrium in which market clears at a price where supply equals demand. The next section presents how the electrical energy trade is organized and the functioning of open electricity markets.

2.2 Open Electricity Markets

2.2.1 Bilateral Trading

This type of trading is only between two parties (sellers and buyers). These two parties set the price of the transaction independently. Hence there is no official price involved[9]. E. Bompard and M. Yuchao addressed the various types and modelling of bilateral trading as [10].

2.2.2 Electricity Pools

Electricity pools involve a centralized trading of electrical energy where in sellers (generators) and buyers (consumers) submit their offers and bids at a certain price for the period. Independent System Operator (ISO) or Market Operator (MO) then ranks the offer prices of sellers in ascending order and constructs a curve as a function of bid quantity. This curve is called supply curve. In a similar way ISO or MO constructs a curve as a function of bid quantity by ranking the bid prices of buyers in descending order. This curve is known as demand curve. As shown in figure 2.1, 'the intersection of this supply and demand curves determines the market equilibrium'. The accepted bids and offers are called the winners of the market. The winners of the market are informed about the amount of energy they can supply or draw from the market. The advantage of this type of trading is 'centralized form of management'. It not only handles the transactions of electrical energy but also the transmission system responsibility [11-13].

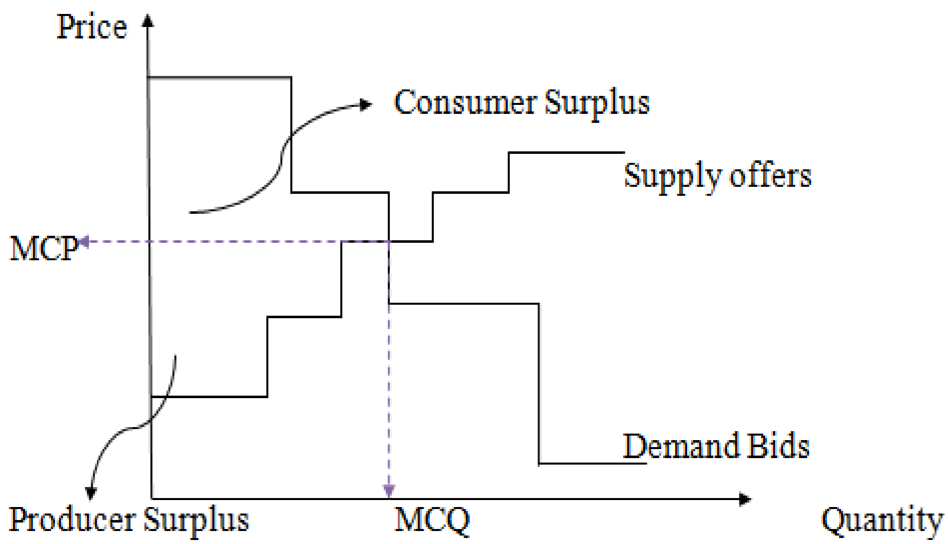

Figure 2.1 Market Clearing Process

2.3 Electricity Pricing

The issue of electricity price forecasting has become very essential for utilities in order to make decisions, plan bidding strategies, scheduling and for reliable operations [14]. Forecasting of electricity market prices is difficult because these prices are highly volatile than other financial markets. The reason of high volatility is due to the fact that electrical supply and demand, unlike other commodities, should be on real-time balance. The other reasons for volatility in electricity market prices may be due to fuel prices, generation problem, transmission constraints, weather problems, bidding strategies of market players, losses etc. There are two methods developed by researchers to forecast these prices [15]. The first method is 'Analysis-based' which makes use of the historical data of market participants to forecast the future electricity market price. The second method is 'Simulation-based' which makes use of system operation internal data like initial offers, constraints of operating system and demand bids to forecast the market price. This method is generally used by market operators and large power utilities. This method is not practical as it requires the internal data of the system under operation.

The profit of utilities depends upon the strategy of providing the required energy with right price at right time [16]. The various pricing methods used in the electricity markets are

Market Clearing Price (MCP): If there are no transmission constraints in a system then MCP is determined by offers and bids submitted by generators and consumers. It's the only price for the entire market system.

When transmission constraints are considered the following types of pricing are used

Locational Marginal Pricing (LMP): It is the cost of supplying 'next MW of load' to a specific location. It takes into account the marginal cost of generation, cost of losses and cost of transmission congestion. Optimal power flow (OPF) with transmission constraints is conducted to balance the demand at different buses and to determine LMP. LMP is different at different buses. It is also known as 'Nodal Pricing' (NP).

Zonal Market Clearing Price (ZMCP): This type of pricing comes into picture when ISO detects congestion along a transmission path in a zone for a given period. ISO then adjusts the zonal scheduling at the two ends of transmission path which relieves the congestion. Thus, a new MCP is determined by OPF at the two ends of the path known as ZMCP.

2.4 Settlement Methods in Electricity Markets

The settlements for market winners in electricity markets are done based on the rules agreed by all market participants. There are two such rules which are economic' i.e.

- **Uniform Pricing Rule:** Bidders submit sealed bids and MO constructs supply-demand curves and determines market clearing price at which supply equals demand. Market winners are paid a price according to MCP.

- **Discriminatory Pricing Rule (Pay-As-Bid):** Bidders submit sealed bids and MO constructs supply-demand curves and determines market clearing price at which supply equals demand. Market winners are paid a price according to their bids.

There are various uniform pricing options that are used in electricity markets based on offers and bids of suppliers and consumers. They are as follows

2.4.1 Last Accepted Offer (LAO) or First Rejected Offer (FRO):

If the demand is inelastic then auction is only adopted for the supply. The supply offers are then ranked in increasing order by the ISO and the energy is dispatched at a point where ranked offers satisfy the demand. Here, the market uniform pricing can be settled either to LAO or FRO. If the energy is dispatched at a point where the block of offer is marginally accepted then this block will be the last accepted block and its price will be the block price of the offer [17].

Figure 2.2 shows uniform pricing options for supply side.

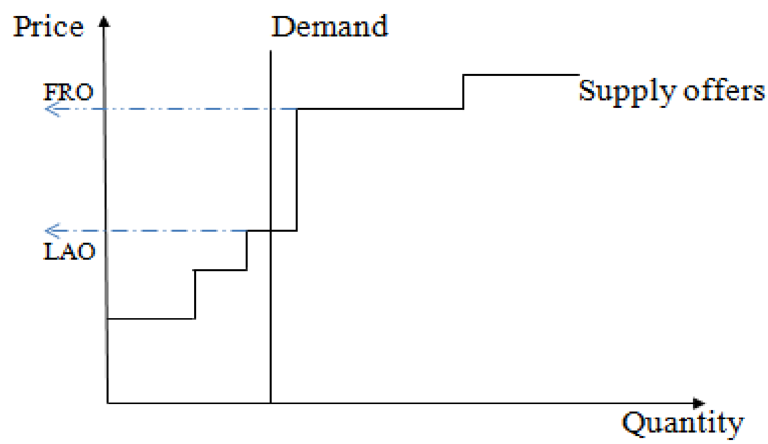

Figure 2.2 Uniform Clearing Prices by supply-side

2.4.2 Last Accepted Bid (LAB) or First Rejected Bid (FRB)

When the supply is inelastic the auctions are only for demand. The demand bids are then ranked in decreasing order with respect to their price by ISO. The energy is dispatched at a point where demand is satisfied as shown in figure 2.3. Here, the market clearing price can be settled to either Last Accepted Bid (LAB) or First Rejected Bid (FRB) [17, 18].

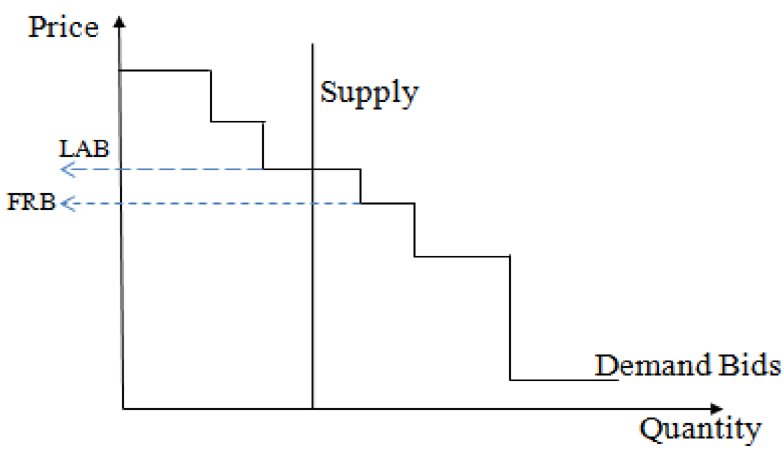

Figure 2.3 Uniform Clearing Prices by Demand-side

2.4.3 Double-Sided Auction Electricity Market

For double-sided auctions in electricity markets, the supply offers and demands bids are ranked in ascending and descending order respectively until the offer price exceeds the bidding price i.e. until demand is satisfied. Figure 2.4 shows the various uniform pricing options used in double sided competitive electricity markets. The uniform price can be set to any value between bid-offer gaps as shown in the figure 2.4. This settlement would be satisfactory for all the market participants. In case of partially cleared block, set this partial cleared block price as uniform price. This block can be either an offer or a bid [18, 19].

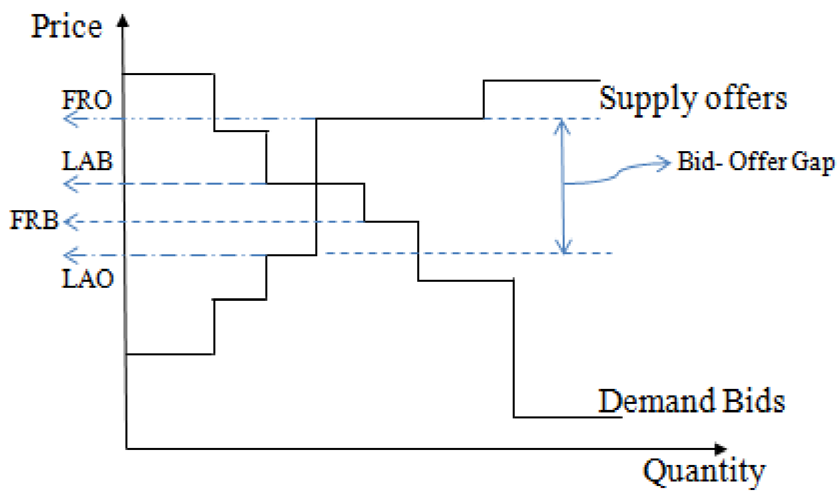

Figure 2.4 Uniform Clearing Prices under double-sided auction electricity markets

2.5 Demand Side Participation (DSP)

Electricity prices in fake markets are decided by the supply side participation. For a competitive market, demand side should also be involved to decide the electricity price. This type of involvement of both supply and demand sides is possible in real market as mentioned in section 2.4.3. In general, the ‘fully competitive electricity market’ should be open for not only generation companies but also for demand entities. It has been documented through research that Demand Side Participation (DSP) makes system reliable and optimal. In china the participation of demand side has provided the fast progress of power industry reconstruction [20-22].

2.5.1 Definition of DSP

One can understand from Demand Side Participation that it is done in order to communicate between “wholesale and retail electricity markets” having an objective of changing the loads depending upon the wholesale electricity price and the load requirement area. There are many ways to define DSP, but its basic function is to make the system reliable and profitable to both supply and demand side participants. DSP encourages customer to reduce their consumption during the period of high price and receive incentives for their participation.

DSP is not only confined to electricity market but also has other applications like ancillary services, reserves and quality control [23-25].

The participation of demand side in electricity are for different purposes like price setting in electricity markets or contracts, easing transmission constraints of a network, market balancing and ancillary services.

2.5.2 Importance of DSP

The effective response of electricity customers is important for following reasons [26-28]

a. During critical periods of supplying the demand, the active DSP reduce the price spikes.
b. The reduction in the demand by DSP during critical periods brings the market to a reliable position by reducing supply from highly expensive generators.
c. When there is an insufficient supply, load shedding can increase system reliability.
d. Regulation and spinning reserves may be provided by load which results in low cost.

Demand response benefits in the improvement of electricity production resource efficiency. The increased efficiency has variety of benefits as follows: [29].

1. It creates a sum of amount to benefit the power plants to use the most "costly-to-run power plants" during the periods of 'high demand'. This drives the prices down for all wholesale electricity purchasers.
2. Customers may earn financial benefits in the form of 'incentive payments' by adjusting their demand with respect to time-varying electricity rates and participants may earn benefits by bill savings.
3. Demand response reduces financial costs and inconvenience to customers by reducing consequences of forced outages. This results in operational security and adequacy savings.

4. ‘Market performance benefits’ i.e. demand response mitigates suppliers’ ability to exercise market power by raising power prices.

2.6 Accomplishment of Demand-Side Participation within Competitive Electricity Markets

The accomplishment of Demand Side Participation in electricity market can be studied in the form of two perspectives.

2.6.1 Retailer’s Perspective

Retailers should be able to forecast its load behavior and should also be able to predict future average electricity prices accurately in order to balance risks associated with buying energy between forward contracts and volatile spot markets and offer consumers appropriate retail supply contracts. The problem of optimal purchase can be addressed by using a stochastic optimization method to purchase allocation-problem for “long-term forward market and short-term spot market”. Based on the optimal purchase allocation, a method is developed for generating demand-side bids [30].

A retailer would ideally like to balance power, it purchased from the day-ahead market or by using long-term contracts, exactly with the consumer’s demand. Due to random consumption behavior of demand this situation is not possibly achieved which imposes risks on the retailer. The retailer is thus forced to sell the imbalanced power on the spot market. The imbalances handling by retailer represents risks as the electrical energy price on the spot market is volatile. To avoid such risks, a retailer should forecast the demand of its customer precisely which is impossible. The retailer must classify its customers into groups having same load profiles and then identity groups and their dependence on meteorological and temporal factors [31, 32]. Also a retailer can focus its efforts in marketing toward high profitable customers by predicting load profiles of these customers on the basis of its type of its load factor, industrial activity, and its annual energy consumption [33].

2.6.2 Customer's Perspective

Consumers subscribe DSP programs due to financial benefits that they can realize from these programs. These programs involve a chain of decisions both before and after subscribing to a DSP option. Benefits like reduced forced outages may also motivate consumers to take part into a DSP option. The decision of a consumer to respond to DSP programs depends on the benefits that the consumer can derive from its participation, the amount of load its able to modify and length of DSP event [34]. The following are the basic strategies for load response during a DSP event:

Foregoing: It involves curtailing load when prices are high compared to some threshold value and service is less than critical point.

Substitution: It means to substitute electrical energy consumption to an alternative resource.

Shifting: It means the ability to change the amount of energy consumed at any given time. 'Load shifting' can be done by turning off a piece of equipment; switching to internal, off-grid power generation sources; or operation of equipment only during off-peak hours.

2.7 Implications of Demand Side Participation

This section discusses implications of DSP in the electricity markets. In general, it has many implications on the market participants and the system as a whole. The retailers and large consumers of electricity make profits from the low wholesale electricity prices during critical periods due to the response of consumers to time-varying loads. A part of this profit must be assigned for the consumers who respond during critical periods of demand [35]. The implementation of DSP needs initial cost for the development of infrastructure and technology along with transition costs. DSP should be implemented only when the benefit derived from DSP is greater than the cost of implementation [36].

Moreover, the reduction in the electricity price due to DSP results in reduced scarcity rents (revenue obtained minus variable operating cost) to the generators. This scarcity rents now relocates to the demand-side. This reduction of rents may lead for generators to bid high for off-peak loads so that it can make up for the loss during peak periods. DSP encourages consumers who do not mind being disconnected totally or partially during emergency periods to serve as a reserve. These consumers would be paid an exercise amount with an option fee for their load being disconnected. This type of operation would secure the system as a whole and provides the essential economic operation. All in all, the concept of DSP provides security during emergency periods and is cost effective because it affects only consumers who wish to participate. But DSP has few disadvantages like; high cost involved in installing remote switching device makes the implementation of DSP limited to large consumers and difficulty to expect the size of load that should be reduced during emergency periods [37, 38].

2.8 Electrical Markets and Transmission Networks

Having studied the electricity markets, electricity pricing and demand side participation, it is important to see how the transmission networks are related to the electricity markets. It is very much tenable to assume that electricity can be traded as if all the generators and loads are connected to a single bus bar. There is a sequence in which electricity is traded into the markets. Generators produce the electricity, transmission system transmits it to the distribution system and finally distributors distribute it to the consumers. During this sequence of operation there may occur power losses and transmission constraints in the network. These transmission constraints and losses by a great mean can introduce distortions into the market. Thus, the role of system operator in such situations becomes very important that it should maintain the energy balance and system security at regular intervals [39].

2.8.1 Decentralized Market and Transmission Networks

In decentralized trading or bilateral trading, only sellers and buyers are involved in energy transactions. In case of transmission constraints, these parties sign an energy trading contract agreeing on a particular quantity to be delivered at a particular time on agreed price and any other conditions. System operator must be informed about such trading. System operator then maintains the system security and energy balance [40]. In order to avoid any interruptions in power transmission between these two parties, the advocates of decentralized market suggest that these parties can own the physical transmission rights. It is the right to use the transmission system for a particular transaction in order to avoid interruption in power through a given transmission link. These rights are owned by auction in the market. The parties must decide themselves whether or not the price linked with this rights is justifiable depending on their location and situations. Once the party owns this right, they can use them or sell them to other parties. This situation might prevent market participants to hoard the transmission capacity for enhancing market power. In practice, enforcing this phenomenon is hard because the path taken by the power in a network is decided by “physical laws but not by the wishes of market participants” [41]. Secondly, the exercise of market power can be exacerbated by some participants. Finally, the unused transmission constraints may be released very lately that the other market participants find difficulty in readjusting their trading positions [42].

2.8.2 Centralized Market and Transmission Networks

In centralized market, producers and consumers submit their supply offers and demand bids to the system operator. System operator, after collecting these offers and bids, optimally clears the market by taking into account the problem of system security imposed due to transmission constraints. These constraints may create congestion in the transmission network. To avoid this congestion consumer may be forced to purchase power from local generators which may be expensive. This congestion divides the market into separate zones resulting in different prices at different locations of a network [43, 44]. These prices are called “locational marginal prices” since the marginal cost is based upon the location where energy is produced or consumed. If these prices are different at different buses of a system then these prices are called as nodal prices [45]. Hence, in centralized electricity market with transmission constraints the price of electrical energy depends on the location or bus where the power is produced or consumed. The role of ISO in centralized electricity market is very essential when compared to bilateral trading.

ISO needs to achieve the economic efficiency by optimally using the transmission constraints [46].

Due to differences in the prices at different buses, a surplus called ‘merchandizing surplus’ may arise. This is always equal to the difference between the prices of producing bus and consuming bus multiplied by the flow on the interconnection between two buses. As this surplus is due to congestion in transmission network it is also known as “congestion surplus”. This surplus is collected by the market operator (MO). However, MO should not keep this surplus with it as this encourages congestion or at least no proper action to be taken towards reducing transmission constraints. If this surplus is returned to the market participants then the concept of nodal marginal prices would go blunt which was designed to encourage achieving economic efficiency [47]. The settlement of congestion surplus is discussed in section 2.10.2.

2.9 Losses in Transmission Networks

Electrical power transmission through an electrical network results in losses. The losses are to be supplied by one or more generators and hence these generators expect to be paid for their production [48]. Therefore, a mechanism must be designed to take into account the cost of losses in the electricity markets. P. O. Oluseyi, et al[49] presents the consequences of losses in Nigeria and the modeling of electricity market.

The prices, that are to be paid to generators because of losses in the network, are shared by the loads at different buses. MO decides the price of losses depending upon the power flow. There is no particular rigorous method to quantify the cost of losses [50].

2.10 Managing Transmission Constraints in Centralized Electricity Markets

It is unusual for the market participants to purchase all the power required through the spot market. In order to avoid fluctuations in electricity prices, which usually occur in the spot market, participants sign contract for differences agreeing on delivery of a certain quantity and at a certain price at a particular period. It is important to see how transmission constraints affect these contracts and what new contractual measures must be taken to manage the congestion risk. Losses also do affect the marginal nodal prices but this affect is small and is predictable [51]. So, this thesis considers only the effect of transmission congestion.

2.10.1 New Contractual Tools

In centralized electricity markets, the energy generated and consumed is traded through the ‘pool’. System Operator receives price for energy consumed at the bus based on its nodal price and pays the price for energy produced at the bus depending upon its nodal pride. In order to avoid vagaries of the nodal prices, market participants are allowed to sign ‘bilateral contracts’. When there is no congestion in the network, the nodal prices almost remain the same depending upon the location. When congestion occurs in the network, different buses have different nodal prices. The contract signed between two parties depending upon their nodal prices may result in incompatible expectations. In general, this contract which covers only the delivery of energy does not work during congestion. In this situation, market participants should not only contract for the energy trading but also for “the ability of transmission system to deliver it” [52, 53].

2.10.2 Financial Transmission Rights (FTRs)

In order to avoid the incompatible expectations resulting in the contract for difference, the parties signing the contract should also hold financial transmission rights (FTRs). FTRs are between two nodes which own the holders of its revenue equal to the product of price difference between two nodes and the capacity of flow through that branch. This is same as the “congestion surplus” that was discussed in section 2.8.2. The amount derived from these rights will be used to settle the contract between two parties. These rights completely isolate the risk associated with congestion in the system. In order to own these rights, participants need to undergo an auction process where in all generators, consumers and speculators can participate in order to gain profit from the locational price differences [54]. The highest bidder of this auction will be given FTRs. The bidder at maximum can submit the difference between the nodal prices as its bid. These FTRs are usually defined from one point of network to any other of the network irrespective of its direct connection through a branch. The matter of concern is only ‘the bus where the power is injected’ and ‘the bus where power should be extracted’; the path of power flow is of no importance. These rights are known as point-to-point FTRs [55].

2.10.3 Flow-Gate Rights

In point-to-point FTRs, the rights are defined from point-to-point. Instead of this, rights can be linked to a branch or flow-gate in the network. These rights are known as Flow-Gate Rights (FGRs). The price of these rights is fixed to a value of ‘langrage multiplier’ or ‘shadow cost’ associated with maximum available capacity of flow-gate [56]. If the branch is not operating at its maximum available capacity then its langrage multiplier is zero. The participants in contract should only own FGRs of congested branches. Only those FGRs can produce revenue which is operating at its highest capacity. The risk associated with FGRs is that the congested branches are difficult to be predicted. The owner of FGRs never pay money back to the MO since Langrage multiplier is never negative [57].

2.11 Strategic Bidding in Electricity Markets

In double-sided auction competitive electricity markets, market participants face the problem of bidding because it's their bidding strategy which defines them as either a market winner or loser. Whereas, in bilateral trading there is no such strategy but it requires the necessity of price negotiation between the parties. Therefore, market participants construct their bidding strategy in order to avoid risks and maximize their social welfare by trading through pool markets. Hence, Strategic bidding can be defined as the process by which the market participants aim to achieve their performance goals by developing bids. System operator encourages such competitive bidding processes to achieve the cost-minimizing function. While each market participant develops bidding strategy using rivals historical data to maximize the profit [58]. Market price and electricity trade depend on bidding strategies of market participants. The various factors that should be considered when providing the power quantity and price bids are

a. Load patterns (daily, weekly and seasonal).
b. Generation technical limits.
c. Demand prediction.
d. Previous market clearing prices.
e. Maintenance of generators and lines etc.

The winners of market will be paid or pay on the basis of rules agreed in the electricity market. It either follows uniform or PAB pricing, discussed in chapter 2, section 2.4.

Market participants analyze and construct their bidding strategy using several approaches or techniques. The following are the few techniques used by the participants.

a. Optimization-based technique: In this technique, the rivals in the electricity market are modeled stochastically or deterministically using probability distribution functions. This approach uses the historical data of rivals participating in the market. Then different bidding strategies using various factors such as risk factors, retail price, interruptible price and correlation coefficient are studied. Finally, optimal bidding strategy is determined from the various designed scenarios [59].
b. Equilibrium-based approach: In this category, rivals are considered in determining game theoretic equilibrium of market[60].
c. Learning-based approach: In this category, learning algorithms are applied to bidding strategy problem. Due to electrical market complexities, it is more effective since it learns from the empirical data [61].

Technique (a) is used in this thesis wherein Monte-Carlo Simulation and GA tools are applied to build an optimal bidding strategy for an LSE.

2.11.1 Bidding Strategies for Electricity Producers

Electricity producers can build their optimal bidding strategies in three ways.

The first way is to believe that its energy offering will not influence market price and thus it acts as a price taker. In this case, producer will determine its bidding strategy based on the estimation of MCP. Once, it estimates the MCP it will offer the energy at a price little cheaper than MCP. Analysis of forecasted load, transmission constraints and behavior of participants will help the producer to estimate the MCP. But, this method will not hold for a longer time since the historical data available is very little in the market and also the assumption that its behavior will not affect or influence the market is implicit.

The second way is to believe that supplier's strategy of energy offering will influence the market but assumes that rivals bids or offers as known from historical data available. This method models the rivals stochastically or deterministically into a bi-level optimization problem. For the first level, supplier tries to maximize its profit under the constraints and for the second level ISO finds an OPF to minimize the system cost. Monte-Carlo Simulation and GA tools are applied to find the optimal bidding behavior of the supplier.

Finally, the third way is to believe that its energy supplying strategy will influence the market and considers the bidding strategy of rivals who also tries to maximize their profit. In this method, supplier should have the information of rivals generation cost and consumers load behaviors. This approach is hard and requires gaming to construct the optimal bidding strategy. But, once constructed this method is the most reliable [62, 63].

2.11.2 Bidding Strategies for Electricity Consumers

As mentioned before, Independent Load Serving Entity (LSE) will compete with other LSEs and suppliers in double-sided auction electricity market. LSEs submit the offers for purchasing electricity through pool trading to ISO. Like suppliers, the profits of LSEs also depend on their bidding strategies to a certain extent. These strategic biddings of LSEs might show some significant impacts on electricity markets. Demand Side Bidding (DSB) is a strategy that enables the demand to actively participate in the trading of electricity [62, 63].

Several researchers have developed bidding strategies for LSEs using a day-ahead market. Stochastic processes and Nash-cournot techniques are used to model market participants. This thesis uses ‘step wise bidding functions and pay-as-bid settlement protocols’ to develop an optimal bidding strategy for LSEs. Last Accepted Bid (LAB) pricing rule is used to determine MCP. Bidding behaviors of the market participants (rivals) are described by a normal probability distribution function, and a stochastic optimization model is used to formulate the issue of constructing optimal strategic bidding for LSEs. Monte-Carlo approach is applied to get the corresponding solutions. Finally Genetic Algorithm (GA) is applied to get the optimal solution out of Monte-Carlo Simulation solutions[64].

CHAPTER 3

MATHEMATICAL MODELING FOR LOAD SERVING ENTITIES

This chapter develops a mathematical model for an LSE in pool-based double-sided competitive electricity market. The market uses 'step-wise price/quantity bidding functions and PAB settlement' with LAB pricing rules. The trading for electric power is done daily dividing each day into 24 trading periods. Bidding for next 24 periods is done before the next day starts [64].

3.1 Mathematical Modeling of an LSE in Electricity Market

Considering two models of electricity market pools without and with transmission constraints, a bidding strategy for the LSE is developed. These models consist of Y 'independent Gencos' and Z 'independent LSEs'. One out of the available LSEs, suppose X, is considered to build the optimal bidding strategy. Hence the rivals of this LSE are Y+Z-1. "Each generation company bid at most Ig blocks for each period; the block price must be non-decreasing with the increase of the block number. Each LSE bid at most Id blocks for each period, the block price must decrease with the increase of the block number. The market operator (MO) receives selling energy bids from Gencos and buying energy bids from LSEs and then determines the generation dispatching level of every Genco and the demand dispatching level of every LSE for every trading period and also the market clearing price (MCP)" [64, 65].

Suppose the forecasted load for each type of load is q_{Xj}

Where, X represents the LSE X and $j = \text{No. of blocks} = 1,2 \ldots\ldots$ Id

The process of bidding for the selected time period will be as follows:

$Q_{d,X}^{j}$ – Block quantity for each type of load

$\bar{Q}_{d,X}^{j}$ – Cleared block quantity for each type of load

$p_{d,X}^{j}$ – Cleared block price for each type of load After Market Clearing Process

Retail price: It is the price at which LSEs would sell the power to the end customers. Its unit is \$. The thesis uses retail price as 'a' \$ per MW.

Interruptible price: It is the price that LSEs would pay to the end customers in case of any interruption in power supply. Its unit is \$. The thesis uses interruptible price as 'b' \$ per MW.

The block prices and quantities can be represented as:

$$p_{d,X} = (p_{d,X}^{1}, p_{d,X}^{2}, p_{d,X}^{3} \ldots\ldots p_{d,X}^{Id}) \tag{3.1}$$

$$\bar{Q}_{d,X} = (\bar{Q}_{d,X}^{1}, \bar{Q}_{d,X}^{2}, \bar{Q}_{d,X}^{3} \ldots\ldots \bar{Q}_{d,X}^{Id}) \tag{3.2}$$

The objective of this model is to find the maximum profit for LSE with optimal bidding strategy. Hence the profit of LSE X can be described as

$$\pi = R(\bar{Q}_{d,X}) - p_{d,X}(\bar{Q}_{d,X})^{T} - f(\bar{D}_{DX}) \tag{3.3}$$

Where,

π is the profit of LSE X in one unit time

$R(\bar{Q}_{d,X})$ is the retail income

$f(\bar{D}_{DX})$ is the maintenance cost of distribution system

$\bar{D}_{DX}$ is the dispatched demand power

The retail income of the LSE X is equal to the revenue from sold power to end customers minus the expense of interrupted power to end customers, illustrated as

$$R(\bar{Q}_{d,X}) = a(\bar{Q}_{d,X})^{T} - b(Q_{d,X} - \bar{Q}_{d,X}) \tag{3.4}$$

Using (3.4) in (3.3) we get

$$\pi = a(\bar{Q}_{d,X})^{T} - b\left(Q_{d,X} - \bar{Q}_{d,X}\right)^{T} - p_{d,X}(\bar{Q}_{d,X})^{T} - f(\bar{D}_{DX}) \tag{3.5}$$

The problem for building an optimal bidding strategy for LSE X is to maximize its profit. So to find optimal solution, the risks involved in the market should also be taken into account. According to investment theory, the variances of the potential profit can be used to evaluate the risks of an investment. Hence the problem is formulated as the following stochastic optimization problem [64-66].

$$\delta = \alpha_1 E(\pi) - \alpha_2 D(\pi) \tag{3.6}$$

Subject to:

$$E(\pi) = a(\bar{Q}_{d,X})^{T} - b\left(Q_{d,X} - \bar{Q}_{d,X}\right)^{T} - p_{d,X}(\bar{Q}_{d,X})^{T} - f(\bar{D}_{DX}) \tag{3.7}$$

$$\sum_{j=1}^{Id} \bar{Q}_{d,X}^{j} = \bar{D}_{DX} \tag{3.8}$$

$$p^{j+1} \leq p^{j} \tag{3.9}$$

$$p^{j} \geq P_{min} \tag{3.10}$$

$$0 < \alpha_1 < 1 \tag{3.11}$$

$$\alpha_2 \geq 0 \tag{3.12}$$

Where,

$E(\pi)$ is the expected value of profit π

$D(\pi)$ is the standard deviation

α_1 and $\alpha_2$are used to represent the degree of risk

$\alpha_1 = \alpha$ and $\alpha_2 = 1 - \alpha$

The above optimization problem cannot be solved directly as the LSE X does not know the bidding parameters of rivals before the sealed auction. The bidding parameters of rivals can be estimated using the historical bidding data and load forecast. The bidding behavior represents a stochastic process can be represented as Bivariate Normal Distribution (BND) where each rival form both Gencos and LSEs has to submit block bidding with two values containing quantity and price [64-66]. Bidding behavior of Gencos has $\tilde{Q}_{g,k}^{l} \sim N(\mu_{\tilde{Q}_{g,k}^{l}}, \sigma^2{}_{\tilde{Q}_{g,k}^{l}})$ and $\tilde{p}_{g,k}^{l} \sim N(\mu_{\tilde{p}_{g,k}^{l}}, \sigma^2{}_{\tilde{p}_{g,k}^{l}})$ which follows the bivariate normal distribution defined by the probability density function as

$$f(\tilde{Q}^{l}_{g,k}\ ,\tilde{p}^{l}_{g,k}) = \frac{1}{2\pi\sigma_{\tilde{Q}^{l}_{g,k}}\sigma_{\tilde{p}^{l}_{g,k}}\sqrt{1-\rho^2}}\exp[-\frac{1}{2(1-\rho^2)}[\left(\frac{\tilde{Q}^{l}_{g,k}-\mu_{\tilde{Q}^{l}_{g,k}}}{\sigma_{\tilde{Q}^{l}_{g,k}}}\right)^2 + \left(\frac{\tilde{p}^{l}_{g,k}-\mu_{\tilde{p}^{l}_{g,k}}}{\sigma_{\tilde{p}^{l}_{g,k}}}\right)^2 - 2\rho\left(\frac{\tilde{Q}^{l}_{g,k}-\mu_{\tilde{Q}^{l}_{g,k}}}{\sigma_{\tilde{Q}^{l}_{g,k}}}\right)\left(\frac{\tilde{p}^{l}_{g,k}-\mu_{\tilde{p}^{l}_{g,k}}}{\sigma_{\tilde{p}^{l}_{g,k}}}\right)]] \quad (3.13)$$

(3.13) can be summarized in matrix form as

$$((\tilde{Q}^{l}_{g,k}\ ,\tilde{p}^{l}_{g,k}) \sim N\{\begin{bmatrix}\mu_{\tilde{Q}^{l}_{g,k}}\\ \mu_{\tilde{p}^{l}_{g,k}}\end{bmatrix}\begin{bmatrix}\sigma^2{}_{\tilde{Q}^{l}_{g,k}} & \rho^{l}_{g,k}\sigma_{\tilde{Q}^{l}_{g,k}}\sigma_{\tilde{p}^{l}_{g,k}}\\ \rho^{l}_{g,k}\sigma_{\tilde{Q}^{l}_{g,k}}\sigma_{\tilde{p}^{l}_{g,k}} & \sigma^2{}_{\tilde{p}^{l}_{g,k}}\end{bmatrix}\}) \quad (3.14)$$

Where, $k = 1,2,3,\ldots\ldots Y,\ l = 1,2,3,\ldots\ldots Ig$

On the other hand, bidding behavioral form of LSEs has $\tilde{Q}^{j}_{d,i} \sim N(\mu_{\tilde{Q}^{j}_{d,i}}, \sigma^2{}_{\tilde{Q}^{l}_{g,k}})$ & $\tilde{p}^{j}_{d,i} \sim N(\mu_{\tilde{p}^{j}_{d,i}}, \sigma^2{}_{\tilde{p}^{j}_{d,i}})$ which follows the bivariate normal distribution and defined by the probability density function as

$$f(\tilde{Q}^{j}_{d,i}\ ,\tilde{p}^{j}_{d,i}) = \frac{1}{2\pi\sigma_{\tilde{Q}^{j}_{d,i}}\sigma_{\tilde{p}^{j}_{d,i}}\sqrt{1-\rho^2}}\exp[-\frac{1}{2(1-\rho^2)}[\left(\frac{\tilde{Q}^{j}_{d,i}-\mu_{\tilde{Q}^{j}_{d,i}}}{\sigma_{\tilde{Q}^{j}_{d,i}}}\right)^2 + \left(\frac{\tilde{p}^{j}_{d,i}-\mu_{\tilde{p}^{j}_{d,i}}}{\sigma_{\tilde{p}^{j}_{d,i}}}\right)^2 - 2\rho\left(\frac{\tilde{Q}^{j}_{d,i}-\mu_{\tilde{Q}^{j}_{d,i}}}{\sigma_{\tilde{Q}^{j}_{d,i}}}\right)\left(\frac{\tilde{p}^{j}_{d,i}-\mu_{\tilde{p}^{j}_{d,i}}}{\sigma_{\tilde{p}^{j}_{d,i}}}\right)]] \quad (3.15)$$

(3.15) can be represented in matrix form as

$$((\tilde{Q}^{j}_{d,i}\ ,\tilde{p}^{j}_{d,i}) \sim N\{\begin{bmatrix}\mu_{\tilde{Q}^{j}_{d,i}}\\ \mu_{\tilde{p}^{j}_{d,i}}\end{bmatrix}\begin{bmatrix}\sigma^{2}{}_{\tilde{Q}^{j}_{d,i}} & \rho^{l}_{d,k}\sigma_{\tilde{Q}^{j}_{d,i}}\sigma_{\tilde{p}^{j}_{d,i}}\\ \rho^{l}_{d,k}\sigma_{\tilde{Q}^{j}_{d,i}}\sigma_{\tilde{p}^{j}_{d,i}} & \sigma^{2}{}_{\tilde{p}^{j}_{d,i}}\end{bmatrix}\}) \tag{3.16}$$

Where, $i = 1,2,3, \ldots\ldots Z-1$, $j = 1,2,3, \ldots\ldots Id$

'ρ' is the correlation coefficient.

μ and σ^2 represents the mean and variance of the quantity and price for for both Gencos and LSEs.

The correlation coefficient between Q *and* p with expected values μ_Q *and* μ_p and standard deviations σ_Q *and* σ_p is their covariance normalized by their standard deviation, as follows

$$\rho_{Q,p} = \frac{cov(Q,p)}{\sigma_Q\sigma_p} \tag{3.17}$$

3.2 Monte Carlo Simulation Method

Monte Carlo methods solve a variety of mathematical problems by using continuously generated random numbers and probability theory. The solution obtained by this method is only the approximate solution to the problem. Thus, Monte-Carlo Simulation can be defined as "statistical simulation methods where statistical simulation is defined in quite general terms to be any method that utilizes sequences of random numbers to perform the simulation". The basic idea of Monte-Carlo Simulation is that if series of samples are not exactly distributed according to the density function then it is likely that the deviation will be small at least for large number of samples. Therefore, mean of arbitrary number of samples should be approximately equal to the expectation value [67, 68] . Monte-Carlo Simulation can be applied in electricity markets to get the expected behavior of the electricity market by investigating how the electricity market will work in a number of less or more randomly chosen scenarios. The advantage of this method is that it is quite straight forward to include market strategies and market designs. The only disadvantage is that it requires a lot of computation[68].

In an experiment of double-sided competitive electricity market, expectation value of profit for LSE X when it adopts bidding strategy is given by,

$$E(\pi) = \left(\frac{1}{T}\right) \sum_{i=1}^{T} \pi(\, s_t) \tag{3.18}$$

Where,

s_t is the t_{th} random sampling value.

T is the 'total random sampling number'

$\pi(s_t)$ is the profit of LSE X of the t_{th} random sampling value

The scatter degree of samples $\pi(s_t)$ can be described by standard deviation as

$$D(\pi) = \sqrt{\left(\frac{1}{T-1}\right) \sum_{i=1}^{T} [\pi(s_t) - E(\pi)]^2} \tag{3.19}$$

If the scatter degree is small, the fluctuation level of the expectation profit is small which means bidding strategy has small risks and if the scatter degree is large then the fluctuations in the expectation profit will be large resulting in serious or large risks.

A coefficient called mutation coefficient is used to measure the level of risk relatively with the expected value of profit. Mathematically it can be stated as,

Mutation Coefficient $K_{ED} = \left(\frac{D(\pi)}{E(\pi)}\right) * 100\%$ (3.20)

3.3 Optimization by Genetic Algorithm

Genetic Algorithm (GA) is a technique for a problem which continuously modifies the population of individual solutions. GA, step by step, produces children for the next generation using individuals randomly from the current population commonly known as parents. This process of evolution will continue towards an optimal level giving an optimal solution to a problem. Thus, it can be defined in a general way as "a method to solve both constrained and unconstrained optimization problems that is based on natural selection, the process that drives biological evolution". Problems in which objective functions are stochastic, non-differentiating, non-linear can be solved by GA [69]. Two types of GA are mainly used to find the optimal solution for problems, they are binary code GA and real coded GA. Binary coded GA is used to code chromosomes and is known to be a popular method. Whereas, real coded GA is more effective in the real world when compared to binary coded GA because binary coded GA has problems like encoding and decoding [70].

The steps in which GA works are

1. Contribution to next generation by selecting individuals from the current population called parents.
2. Generation of children by combining two parents.
3. Applying random changes to individual parents to form children.

Once the bidding strategies for LSE X are developed, the GA optimization is applied in order to get step by step optimized bidding strategy for LSE X[71].

3.4 Procedure for Optimal Bidding Strategy

The procedure of building optimal bidding strategy for an LSE X in an electricity market is listed as follows:

1. Specify the parameters of rivals' probability distribution functions (pdfs) as in equations (3.14) and (3.16).
2. Execute Monte-Carlo simulation as follows:
   a. Specify the random sampling number 'T'.
   b. Specify the offering parameters of Gencos $(\tilde{Q}_{g,k}^{l}\ ,\ \tilde{p}_{g,k}^{l})$ and bidding parameters of LSEs $(\tilde{Q}_{d,i}^{j}\ , \tilde{p}_{d,i}^{j})$ as in equations (3.14) and (3.16).
   c. Determine the market clearing quantity and market clearing price from market clearing process.
   d. Calculate $\pi(s_t)$.
   e. Calculate the expectation profit $E(\pi)$ and standard deviation $D(\pi)$ using equation (3.18) and (3.19).
   f. Calculate the net profit δ using equation (3.6).
3. Create a genetic algorithm whose population members represent the risk factor α, bidding price *p*, standard deviation $D(\pi)$, retail price *a* and interruptible price *b.*
4. Initialize GA population and maximum number of generation, *Tgen.*
5. Set GA generation counter *tgen = 0.*
6. Regard δ as the fitness function of the population members.
7. Perform the standard GA operators, i.e. parent selection, crossover, mutation, etc.
8. Set *tgen* = *tgen* +1
9. If *tgen* < *Tgen.* go back to 5; otherwise go to 10.

10. Find the fittest member of the genetic algorithm as the optimal bidding strategy.

11. Stop

The first two steps represent the Monte-Carlo Simulation for the model, while the steps from 3 to 10 represent GA optimization.

Figure 3.1 shows a flowchart for the procedure of optimal bidding strategy of an LSE in electricity market.

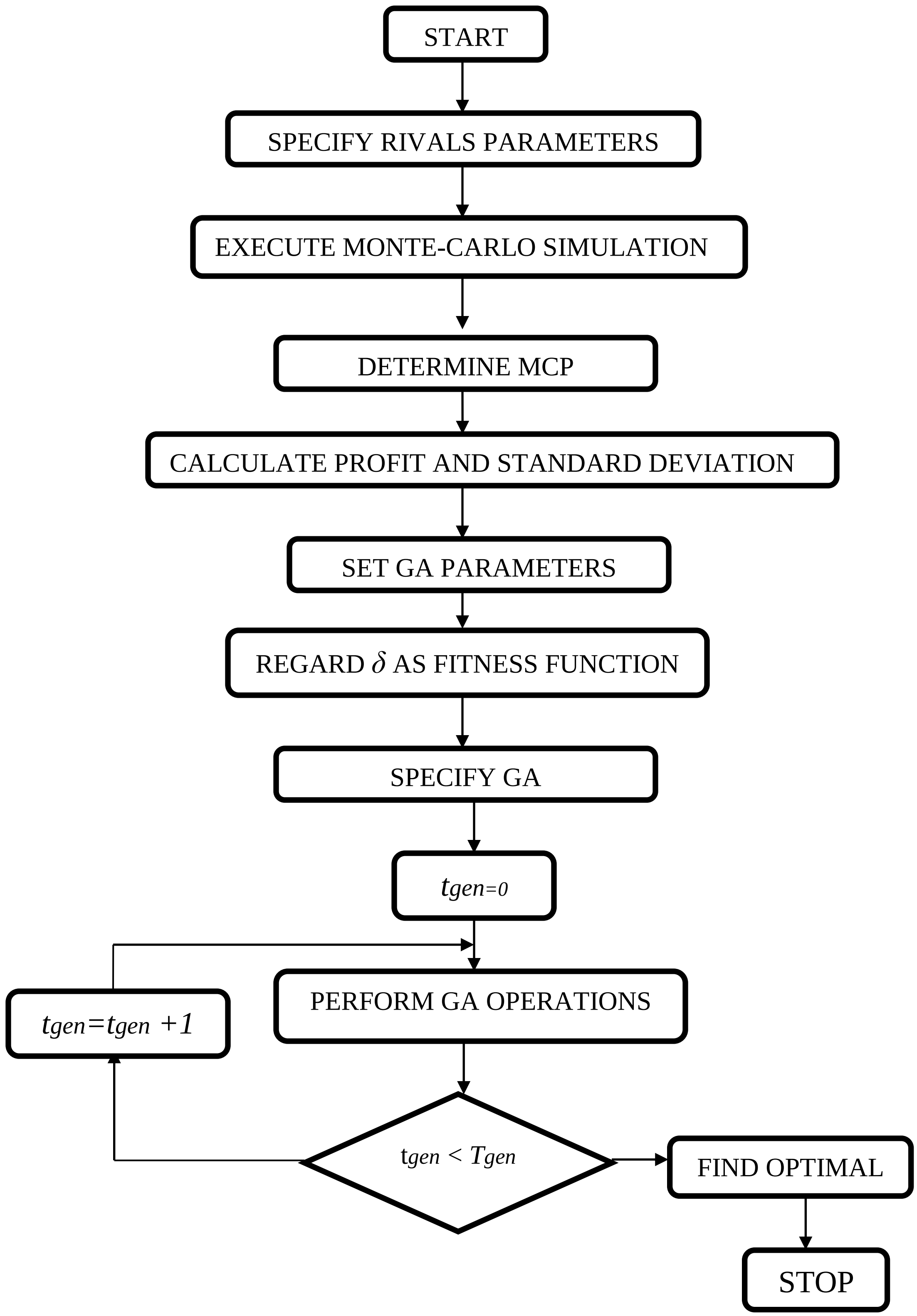

Figure 3.1 Flow chart for Optimal Bidding Strategy

CHAPTER 4

SIMULATION AND ANALYSIS

This chapter is divided into two parts. The first part discusses the simulation and analysis on building an optimal bidding strategy for an LSE in an electricity market without transmission constraints. This market consists of 3 Gencos and 4 LSEs. The second part presents the simulation and analysis on optimal bidding strategy for an LSE using IEEE-30 bus system market model with transmission constraints.

4.1 Optimal Bidding Strategy without Transmission Constraints

Consider a model without transmission constraints, with Y=3 Gencos and Z= 4 LSEs as shown in figure 4.1. LSE X out of 4 LSEs is selected to build optimal bidding strategy which means the number of rivals for LSE X is Y+Z-1 = 6.

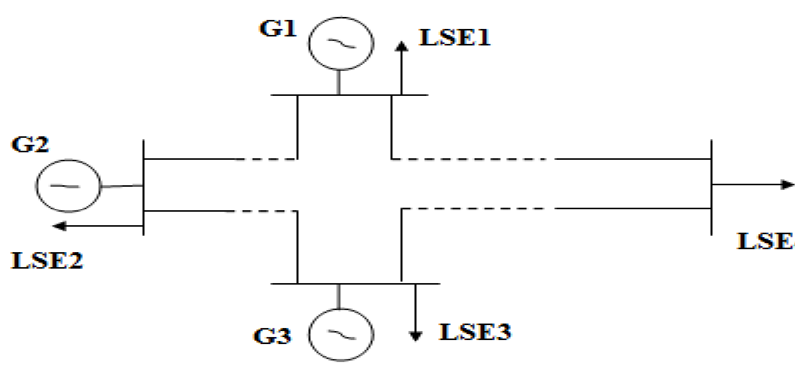

Figure 4.1 Single line diagram of a market model with 3 Gencos and 4 LSEs

The distribution system maintenance cost function of LSE X is taken as [64-66]

$$f(\overline{D}_{DX}) = 13.5 + 1.3\overline{D}_{DX} + 0.0115\overline{D}_{DX}^2 \tag{4.1}$$

$f(\overline{D}_{DX})$ represents the cost that an LSE X has incurred while maintaining technical and administrative actions, including supervision actions, intended to restore the system to a state in which it can perform a required function.

Each market participant is allowed to bid at most 3 blocks (Ig=3 and Id=3)

For each type of load for LSE X, let the forecasted load be 200MW

Therefore, total demand for LSE X = 600MW

Also let, $70 \leq a \leq 140\ and\ 55 \leq b \leq 95$ [64-66]

The minimum bidding block price of LSEs determined by MO is $P_{min} = 20$

Table 4.1 shows the estimated parameters for 3 Gencos [64-66]. μ(qty) in Table 4.1 represents the mean value of bidding quantity with a standard deviation of σ(qty). Similarly, μ(prc) represents the mean value of bidding price with a standard deviation of σ(prc). Table 4.1 also shows that the bidding prices for Gencos are increasing from one block to the another block, i.e. it is \$15 for Genco 1 during block 1 then \$35 during block 2 and finally \$50 during block 3. The other Gencos also follow the same increasing block prices for their supplied capacity.

Table 4.1 offering parameters for 3 Gencos

Genco	Block1		Block2		Block3		Variance	
	μ(qty) (MW)	μ(prc) ($)	μ(qty) (MW)	μ(prc) ($)	μ(qty) (MW)	μ(prc) ($)	σ (qty) (MW)	σ(prc) ($)
1	300	15	200	35	400	50	5.5	2.5
2	200	25	300	45	400	60	5.5	2.5
3	200	55	400	73	300	95	5.5	2.5

Table 4.2 shows the estimated parameters for 3 LSEs [64-66]. μ(qty) in Table 4.2 represents the mean value of bidding quantity with a standard deviation of σ(qty). Similarly, μ(prc) represents the mean value of bidding price with a standard deviation of σ(prc). Table 4.2 also shows that the bidding prices for LSEs are decreasing from one block to the another block, i.e. it is $63 for LSE 1 during block 1 then $43 during block 2 and finally $23 during block 3. The other LSEs also follow the same decreasing block prices for their supplied capacity.

Table 4.2 Bidding parameters for 3 LSEs

LSE	Block1		Block2		Block3		Variance	
	μ(qty) (MW)	μ(prc) ($)	μ(qty) (MW)	μ(prc) ($)	μ(qty) (MW)	μ(prc) ($)	σ (qty) (MW)	σ(prc) ($)
1	100	63	300	43	200	23	5.5	2.5
2	190	85	230	65	180	48	5.5	2.5
3	150	93	220	73	230	43	5.5	2.5

4.1.1 Pool-based Power Market for Different Participants

Pool-based power market is built for one unit time to determine market clearing price and market clearing quantity for all participants. First, rearrange the offers of Gencos in ascending order by the block price and then rearrange the bids of LSEs in descending order by block price. After that, dispatch the selling energy bids and buying energy bids until the buying price is just less than or equal to selling price. Last Accepted Bid method is employed to get the market clearing price and market clearing quantity. The pool-based market built for above model is shown in figure 4.2.

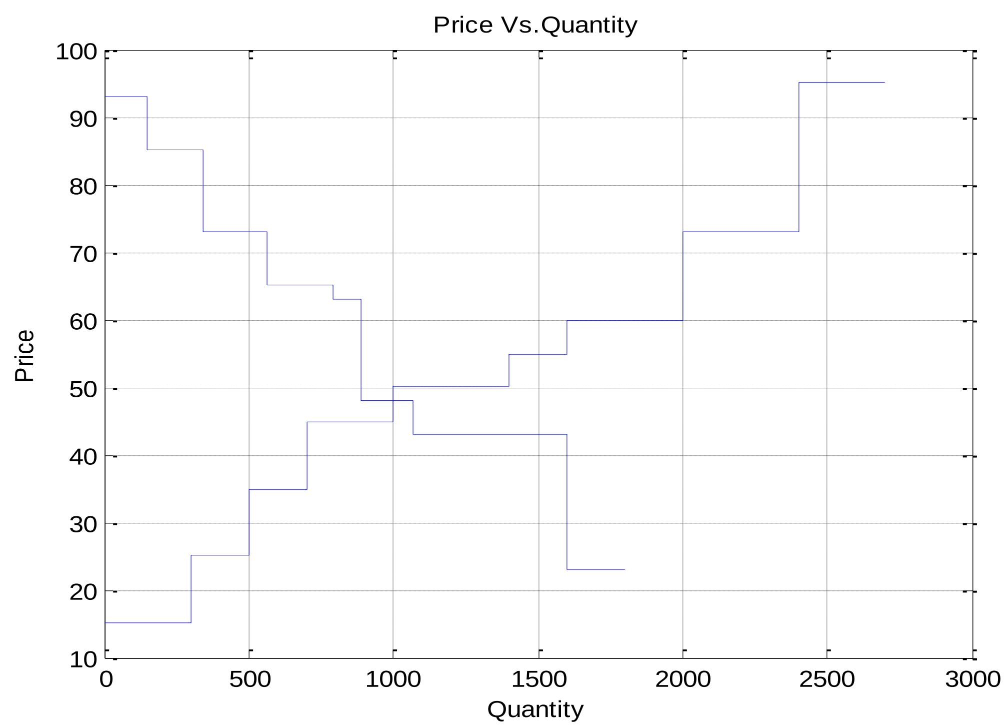

Figure 4.2 Market Clearing Process

Market Clearing Price: $48.056

Market Clearing Quantity: 1070 MW

Market clearing price and quantity obtained from pool-based power market gives the idea of how to bid in the market to clear required quantity. LSE X should bid above market clearing price i.e., \$48.056 to be a market winner. Bidding of LSE X decides how much quantity it can clear from the market. Different bidding strategies for selected LSE X are studied using Monte-Carlo Simulation which calculates expectation profit and standard deviation for each bidding strategy of the LSE. The effect of various factors like correlation coefficient, risk factor, retail price and interruptible prices on bidding strategy of the LSE will be studied step by step. The building of optimal strategy for the LSE X in this thesis is divided into two types of blocks per unit time.

1. Single bidding block per unit time
2. Three bidding blocks per unit time

At first, optimal bidding strategy is constructed using single bidding block per unit time then it is constructed for three bidding blocks per unit time. Finally, the strategies are compared and the observations are documented.

Single Block Bidding per Unit time

The LSE X will bid only single price for all the blocks to clear 600 MW.

4.1.2 Selection of Correlation Coefficient for Bidding Strategy

The correlation coefficient represents the relation between two random variables (here, quantity and price of Gencos/LSEs) with expected and standard deviation values of price and quantity. For an example, as shown in Table 4.3, the first value of correlation coefficient represents correlation coefficient of Gencos and the second value of correlation coefficient represents the correlation coefficient of LSEs. Negative sign in the table shows that the price and quantity are negatively related i.e. price increases as quantity is required.

Initially, the retail price is set to \$100 and the interruptible price is set to \$75. Maximum number of random samplings is set as$T = 5000$. The bidding strategies of rivals are described according to equations 3.14 and 3.16 [64-66]. Different combinations of correlation coefficients are used with same values but different signs. Table 4.3 shows the impact of various correlation coefficients on bidding strategies of LSE X. K_{ED} represents the relative risk level as represented in equation 3.20.

Table 4.3 Impact of Correlation coefficient on bidding strategies

Correlation coefficient (ρ)	MCP ($)	Expected profit ($)	Standard Deviation($)	Net Profit ($)	K_{ED} %
0 and 0	62.939	14322	2184	12671	15.249
-0.1 and 0.1	63.056	14306	2170.5	12658	15.171
-0.1 and 0.5	62.949	14316	2176.6	12667	15.204
-0.9 and 0.9	63.013	14304	2185.5	12655	15.28
0.9 and -0.9	63.054	14315	2187.2	12665	15.279
0.5 and -0.1	63.06	14253	2175.1	12610	15.261
0.1 and -0.1	63.012	14324	2174.3	12673	15.249
0.1 and 0.1	63.096	14327	2182.6	12676	15.234
0.5 and 0.5	62.934	14309	2190.7	12659	15.31
0.9 and 0.9	63.01	14321	2186.6	12671	15.268

The results of various combinations of generator and LSE correlation coefficients show that the impact of correlation coefficient was on the market clearing level and standard deviation. Out of all the combinations above, this thesis uses -0.1 and 0.1 as the correlation coefficient for generators and LSEs. This combination gives low standard deviation when compared to other combinations.

4.1.3 Impact of Different Bidding Strategies on Expectation Profit and Standard Deviation

Correlation coefficients of generator and LSEs are set to -0.1 and 0.1 respectively. At first, the impacts of different bidding strategies on expected profit and standard deviation of LSE X when it does not include itself into the pool market is studied. LSE X assumes that it clears all the required quantity from the market. This strategy is just to get the clear idea how risks and profits of LSE varies with bidding prices and how should it bid when it includes itself within in the market. The results obtained are shown in the Table4.4.

Table 4.4 Profits under different bidding Strategies

MCP ($)	MCQ (MW)	Bidding Price ($)	Quantity cleared (MW)	Expected profit $E(\pi)$ ($)	Standard Deviation $D(\pi)$ ($)
48.056	1070	50	600	25120	2545.2
48.056	1070	52	600	23920	2504.7
48.056	1070	54	600	22718	2464.1
48.056	1070	56	600	21522	2423.7
48.056	1070	58	600	20324	2383.2

Table 4.4 shows that, as the bidding price increases the expected profit decreases and the deviation also decreases. This means, if the LSE can bid high, the risk level of decision decreases but it also decreases its expected profit. Thus, LSE should make a compromise between expected profit and standard deviation which decides level of risk.

4.1.4 The Impact of Different Participation of LSE X into the Pool-Market

When LSE X involves itself into the pool market by providing bidding blocks, the market now consists of 4 LSEs and 3 Gencos. The total amount of load to be cleared is 600MW. The impacts of different bidding strategies on expected profit and standard deviation of the LSE X, when participating into the market are shown in Table4.5.

Table 4.5 Different bidding strategies for LSE X

MCP ($)	MCQ (MW)	Bidding Price ($)	Quantity cleared (MW)	Expected profit $E(\pi)$ ($)	Standard Deviation $D(\pi)$ ($)
49.890	1090	50	200	-20872	2575.5
55.997	1290	56	400	188.26	2442.9
63.055	1490	64	600	16663	2294.9
63.007	1490	68	600	14321	2188.4

Table 4.5 shows that when LSE X offer a price of $50 in the pool market it can clear only 200 MW and its expected profit turns out to be negative. The reason for this is that LSE X has to pay the end customers interruptible prices for the un-cleared quantity of 400MW which results in loss. Also table 4.5 shows that as the bidding price increases the quantity cleared increases to require load, thus, the expected value of profit also increases. The deviation decreases with increasing bidding prices resulting in low risks. Once there is no interruptible load, with increase in bidding price the estimated profit decreases since the gap between the retail price to the end customers and bidding price decreases.

4.1.5 Impact of Different Weighting Factor on Bidding Strategies

LSEs face many risks while adopting bidding strategies because if the bidding price is too low then there is a risk of not clearing the quantity required which reduces the profit of selling electric power to end customers. If the bidding price is too high, then there is a risk of paying unnecessary prices for purchasing electricity. Thus, weighting factor, as a measure of degree of risks is taken into account for building optimal bidding strategies for LSE. Weighting factor (also known as risk factor) is increased from 0.3 to 0.9 and Monte-Carlo Simulation is used to calculate the values of expectation profit and standard deviation results in Table4.6.

Table 4.6 Different Bidding scenarios with respect to weighting factors

$\boldsymbol{\alpha}$	**Quantity cleared (MW)**	**Bidding Price ($)**	**Expected profit $E(\pi)$ ($)**	**Standard Deviation $D(\pi)$ ($)**	**Net Profit ($)**	**KED %**
0.3	200	50	-20846	2518.6	-8016.9	-12.082
0.5	400	56	157.62	2422.1	-1123.9	Not feasible
0.7	600	64	16700	2277.3	11109.2	13.636
0.9	600	68	14305	2197.1	12655	15.359

Negative values of expected profit and net profit in table 4.6 shows that bidding lower price at lower factor of risk will make LSE X undergo loss since the cleared quantity is only 200MW and risk factor is very low. Under this situation, LSE X has to pay the end customers the interruptible prices for un-cleared quantities i.e. 400 MW. Table 4.6 also shows that, when LSE increases its factor of risk, with increasing bidding prices, the profit increases. Thus, LSEs when bidding should always bid high with high factor of risk in order to maximize their net profit. K_{ED} represents the relative risk level. It becomes infeasible i.e. very high when the expected value of profit is very low.

4.1.6 Optimal Bidding Strategy with Weighting Factor

The GA optimization is applied to get the optimal bidding strategy among the results obtained from Monte-Carlo results of all bidding strategies. The parameters associated with GA are specified as Population is 100, mutation probability is 0.1, crossover probability is 0.8 and maximum permitted number of iterations is 100 [64-66]. GA optimization for weighting factor or risk factor (α) ranging from 0 to 1 is shown in Table4.7.

Table 4.7 Optimal bidding strategy with weighting factor

α	0.92914
Bidding Price ($)	63.545
Cleared Quantity (MW)	600
Expected Profit ($)	16118
Standard Deviation ($)	2405.2
Net Profit ($)	14816

Figure4.3 shows the performance of GA while the optimization problem is processed.

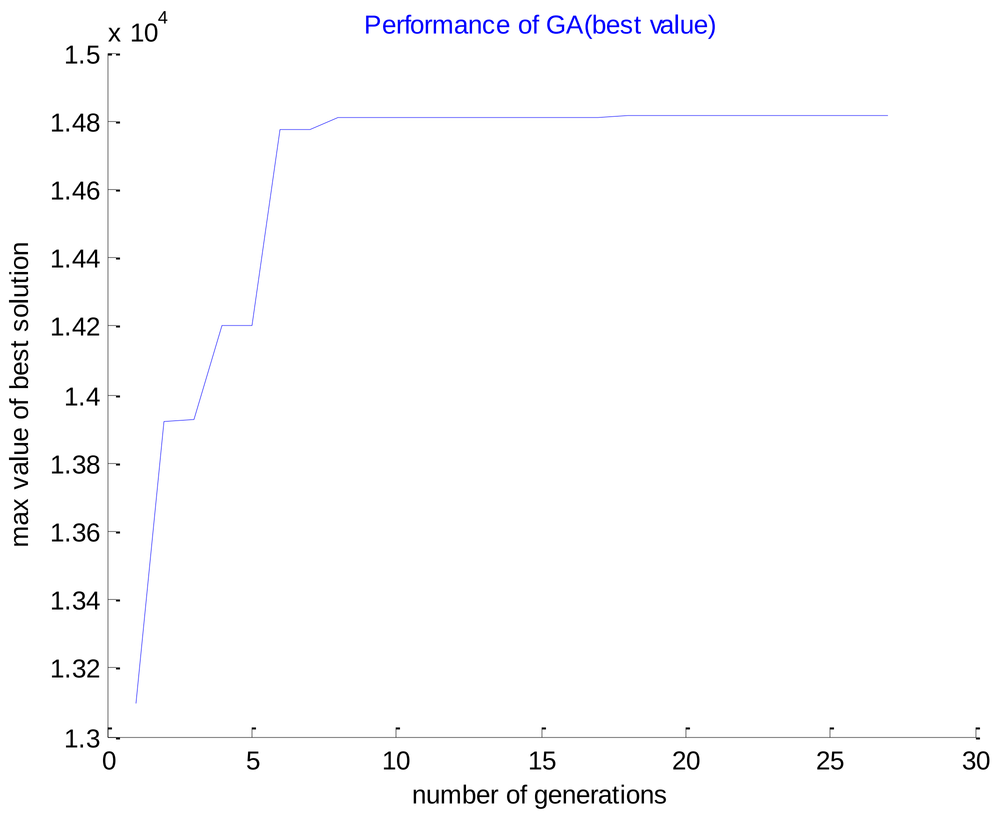

Figure 4.3 Performance of GA

4.1.7 Impact of Retail Price on Profit Maximization

Retail price is the price at which LSEs would sell the power to the end customers. Thus, it is a very important factor for a LSE to maximize its profit. LSE X should choose retail price such that it should neither be too high resulting end customers to look out for other LSEs making LSE X out of business nor the retail price should be too low such that it causes LSE X to incur a loss. Using the results obtained from optimal bidding strategy for weighting factor, i.e. Table4.7; risk factor/weighting factor is set to 0.92914 and interruptible price is set to $75. The values of retail prices are increased from $80 to $140 with increasing bidding prices. Results obtained from Monte-Carlo Simulation are shown in Table 4.8.

Table 4.8 Effect of retail prices on strategic bidding

Retail Price ($)	**Quantity Cleared (MW)**	**Bidding Price ($)**	**Expected profit $E(\pi)$ ($)**	**Standard Deviation $D(\pi)$ ($)**	**Net profit ($)**	**K_{ED} %**
80	200	52	-25286	2123.5	-23644	Infeasible
100	400	56	183.79	2442.3	-2.2978	Infeasible
120	600	60	31134	2769.9	28732	8.8965
140	600	64	40738	3117	37630	7.6514

The reason for negative profit in Table4.8 is due to the dispatch of only 200MW by LSE. LSE should pay end customers interruptible prices for the unsupplied 400MW. Also Table4.8 shows as retail price increases the profit of the LSE X increases and also increases the deviation. The increase in profit is due increased gap between bidding price and retail price. The high retail prices will encourage LSE to bid high in the market to dispatch more power from the market to gain high profits. The increase of retail price may also cause the consumers to choose the other LSEs which offers low retail price.

4.1.8 Optimal Bidding Strategy with Retail Prices

In order to decide whether the increased retail price which gives LSE a large profit is optimal or not, GA optimization is performed with retail price ranging from \$80 to\$140 with same GA parameters as in section 4.1.6. The results obtained for different parameters are shown in Table4.9.

Table 4.9 GA with retail prices as variable member

α	0.97366
Retail price (\$)	128.18
Bidding Price (\$)	63.689
Quantity Cleared (MW)	600
Expected Profit (\$)	33644
Standard deviation (\$)	2366.9
Net profit (\$)	32683

The results obtained from GA optimization shows \$128.18 would be the optimum retail price with 0.97366 weighting factor and \$63.689 as bidding price. The values of expected profit and net profit also seen in the Table 4.9 which are increased when compared to those values in Table4.7 due to increase in retail price.

4.1.9 Impact of Interruptible Price on Profit Maximization

The interruptible prices are the prices which LSE should pay to the end customers in case of interruption in power supply to the customers. Generally, LSEs signs interruptible contracts with end customers which allow LSEs to be secured in case of failing to supply its entire customer load. All they need to do is to pay the agreed financial compensation to the customers.

Values of risk factor and retail price are set to the values obtained in Table4.9. By increasing the values of Interruptible price and bidding prices run the Monte- Carlo Simulation.

Table 4.10 Strategic bidding with various interruptible prices

Interruptible price ($)	Quantity Cleared (MW)	Bidding Price ($)	Expected profit $E(\pi)$ ($)	Standard Deviation $D(\pi)$ ($)	Net profit ($)	K_{ED} %
55	200	52	-7633.5	2718.7	-7504.1	-35.61
65	400	56	13463	2827.6	13034	21.003
75	600	60	36040	2929.3	35013	8.1281
85	600	64	33644	3048.5	32678	9.0608
95	600	68	31246	3202.3	30338	10.249

From table 4.10 initially, the profit is negative because only 200MW were cleared and the LSE has to pay end customers interruptible prices for the un-cleared 400MW, which is a loss for LSE. The results from Table4.10 also shows that as interruptible prices to end consumers increases the deviation increases and the net profit of a LSE increases to a point where in there is no interruptible load. Once, there is no interruptible load, the effect of interruptible prices goes off and profit decreases due to high bidding prices which reduces the gap between retail price and bidding price. Thus, LSE will tend to bid high in the market to dispatch more power in order to avoid high interruptible prices to be paid to end customers in case of failing to provide power to end customers.

4.1.10 Optimal Bidding Strategy by GA with Retail and Interruptible Price

GA optimization is applied with interruptible price ranging from \$55 to \$95 using same GA parameters as in section 4.1.6. Table4.11 shows the optimal GA values obtained.

Table 4.11 GA Optimization with Interruptible Price as a variable member

α	0.90831
Retail price (\$)	139
Interruptible price (\$)	66.52
Bidding Price (\$)	60.859
Quantity Cleared (MW)	600
Expected Profit (\$)	41486
Standard deviation (\$)	2279.7
Net profit (\$)	37415

Table 4.11 shows the GA optimization with weighting factor, retail price and interruptible price taken into account. The optimum interruptible price obtained is \$60.859. The values of expectation profit and net profit are increased when compared to Table 4.9.

4.1.11 Comparison Analysis

Table 4.12 shows a comparison of three scenarios of bidding strategies as discussed in tables 4.7, 4.9 and 4.11. In Scenario1, the retail and interruptible prices are fixed to 100 and 75 respectively. The net profit using Monte-Carlo Simulation method was found to be \$14816. In scenario2, the retail price was changed to \$128.18 by the optimization process where as the interruptible price was still fixed to \$75 and the net profit increased \$ 32683. Finally, in scenario3 retail price and interruptible price were changed to \$139 and \$66.52 respectively by optimization process. The profit in scenario3 increased to \$37415.

Table 4.12 Optimal Bidding Comparison

Factors	Scenario 1	Scenario 2	Scenario 3
Retail price ($)	100	128.18	139
Interruptible price($)	75	75	66.52
α	0.92914	0.97366	0.90831
Bidding price ($)	63.545	63.689	60.859
Quantity Cleared (MW)	600	600	600
Expected profit ($)	16118	33644	41486
Standard deviation ($)	2405.2	2366.9	2279.7
Net profit ($)	14816	32683	37415

As the scenario3 involves high profit and low deviation with low risk value it should be preferred for optimal bidding strategy for single block bidding per unit time.

4.1.12 Comparison with Previous Work

Table 4.13 shows the comparison between different scenarios found in literature survey [71] (highlighted) and the scenarios obtained in table 4.12. Last Accepted Offer (LAO) pricing rule without correlation coefficient was applied while building the optimal bidding strategy for an LSE in literature survey. This thesis uses Last Accepted Bid (LAB) pricing with correlation coefficient to develop an optimal bidding strategy for an LSE. The table 4.13 shows that an LSE applying LAB pricing rule with correlation coefficient has low deviation from its expected profit and thus the net profit is more deterministic and high (as seen in scenario 3 of table 4.12).

Table 4.13 Optimal Bidding Comparison in Previous work

Factors	**Scenario 1**		**Scenario 2**		**Scenario 3**	
Retail price ($)	**100**	100	**138.33**	128.18	**139.54**	139
Interruptible price($)	**75**	75	**75**	75	**80.755**	66.52
α	**0.85817**	0.92914	**087991**	0.97366	**0.81715**	0.90831
Bidding price ($)	**56.477**	63.545	**58.321**	63.689	**56.633**	60.859
Quantity Cleared (MW)	**600**	600	**600**	600	**600**	600
Expected profit ($)	**20479**	16118	**41657.059**	33644	**42808.217**	41486
Standard deviation ($)	**2441**	2405.2	**2411.4**	2366.9	**2336**	2279.7
Net profit ($)	**17228**	14816	**36944**	32683	**35408**	37415

Three Block Bidding Per Unit Time

The LSE will bid single price for each block in increasing order to clear 600MW.

4.1.13 Profits with Different Bidding Strategies

Initially, the retail price is set to $[100, 80, 55] and the interruptible price is set to $[75, 35, 15]. Maximum number of random samples is set to $T = 5000$. Describe the bidding strategies of rivals according to equations 3.14 and 3.16 [64-66]. When LSE X involves itself into the pool market by providing bidding blocks, the market now consists of 4 LSEs and 3 Gencos. The total amount of load to be cleared is 600MW. The impacts of different bidding strategies by LSE X on expected profit and standard deviation, when participating into the market are shown in Table4.14.

Table 4.14 Different bidding strategies for LSE X

Bidding Prices ($)	MCP ($)	Quantity Cleared (MW)	Expected Profit ($)	Standard Deviation ($)
[52,50,48]	51.973	200	-1255.2	2873
[56,52,50]	51.893	400	9515	2759.9
[62,60,52]	59.888	400	7106.4	2624.8
[62,60,54]	53.985	600	9685.3	2593.3

Table 4.14 shows that when LSE X offer a price of $[52, 50, 48] in the pool market it can clear only 200 MW and its expected profit turns out to be negative. Table 4.14 also shows that as the bidding price increases the quantity cleared increases to require load and

interruptible load no more exists, thus, the expected value of profit also increases. The deviation decreases with increasing bidding prices resulting in low risks. Once there is no interruptible load, with increase in bidding price the estimated profit decreases since the gap between the retail price to the end customers and bidding price decreases.

4.1.14 Impact of Different Weighting Factor on Bidding Strategies

LSEs face many risks while adopting bidding strategies because if the bidding price is too low then there is a risk of not clearing the quantity required which reduces the profit of selling electric power to end customers. And if the bidding price is too high, then there is a risk of paying unnecessary prices for purchasing electricity. Thus, weighting factor, as a measure of degree of risks is taken into account for building optimal bidding strategies for LSE. Increasing risk factor from 0.3 to 0.9 and using Monte-Carlo Simulation for the calculation of expectation profit and standard deviation results in Table4.15.

Table 4.15 Different Bidding scenarios with respect to weighting factors

α	Bidding Prices ($)	Quantity Cleared (MW)	Expected Profit ($)	Standard Deviation ($)	Net Profit ($)	K_{ED} %
0.3	[52,50,48]	200	-1258.5	2893.3	-2402.8	Infeasible
0.6	[56,52,50]	400	9513.8	2781.1	4825.7	28.056
0.9	[62,60,54]	600	9684.9	2602.8	8455.3	26.875

Negative values of expected profit and net profit in table 4.15 shows that when bidding lower price at lower factor of risk will make LSE X undergo loss since the cleared quantity is only 200MW and risk factor is very low. Under this situation, LSE X has to pay the end customers the interruptible prices for un-cleared quantities i.e. 400 MW. Table 4.15 also shows that, when LSE increases its factor of risk, with increasing bidding prices, the profit increases. Thus, LSEs when bidding should always prefer to bid high with high factor of risk in order to maximize their net profit. K_{ED} represents the relative risk level. It becomes infeasible i.e. very high when the expected value of profit is very low.

4.1.15 Optimal Bidding Strategy with Weighting Factor

The GA optimization is applied to get the optimal bidding strategy among the results obtained from Monte-Carlo results of all bidding strategies. The parameters associated with GA are specified as Population is 100, mutation probability is 0.1, crossover probability is 0.8 and maximum permitted number of iterations is 100 [64-66]. GA optimization for risk factor ranging from 0 to 1 is shown in Table4.16.

Table 4.16 Optimal bidding strategy with weighting factor

α	0.96699
Bidding price ($)	[61.789,59.577,57.223]
Expected Profit ($)	7228.8
Quantity Cleared (MW)	600
Standard Deviation ($)	2365.8
Net Profit ($)	6904.9

4.1.16 Impact of Retail Price on Profit Maximization

Using the results obtained from optimal bidding strategy for weighting factor, i.e. Table4.16, risk factor is fixed to 0.96699 and interruptible price is fixed to $[75,35,15]. The values of retail prices are increased from $[100, 80, 55] to $[140, 100, 75] with increasing bidding prices. The results obtained from Monte-Carlo Simulation are documented in Table 4.17.

Table 4.17 Strategic bidding with various interruptible prices

Retail Price ($)	Quantity Cleared (MW)	Bidding Price ($)	Expected Profit ($)	Standard Deviation ($)	Net profit ($)	K_{ED}%
[100,80,55]	200	[52,50,48]	-1257.7	2919.6	-1312.5	-232.15
[110,90,65]	400	[56,52,50]	13928	3113.3	13366	22.352
[120,100,75]	400	[62,60,52]	15137	3267.5	14529	21.587
[140,100,75]	600	[64,60,54]	18744	3543	18008	18.902

The reason for negative profit in Table4.17 is due to the dispatch of only 200MW by LSE. LSE should pay end customers interruptible prices for the unsupplied 400MW. Also Table4.17 shows as retail price increases the profit of the LSE X increases and also increases the deviation. The increase in profit is due increased gap between bidding price and retail price. The high retail prices will encourage LSE to bid high in the market to dispatch more power. But the increase of retail price may also cause the consumers to choose the other LSEs which offers low retail price.

4.1.17 The Optimal Bidding Strategy with Retail Prices

In order to decide whether the increased retail price which gives LSE a large profit is optimal or not, GA optimization is performed with retail price ranging from $[100, 80, 55] to$[140, 100, 75] with same GA parameters as in section 4.1.15. The results obtained for different parameters are shown in Table4.18.

Table 4.18 GA with retail prices as variable member

α	0.90128
Retail price ($)	[138.04,96.83,74.37]
Bidding Price ($)	[62.169,59.143,52.538]
Quantity Cleared (MW)	600
Expected Profit ($)	19657
Standard deviation ($)	2147.2
Net profit ($)	17362

The results obtained from GA optimization shows $[138.04, 96.83, 74.37] would be the optimum retail price with 0.90128 weighting factor and $[62.169, 59.143, 52.538] as bidding price. The values of expected profit and net profit also seen in the Table 4.17 which are increased when compared to those values in Table 4.16 due to increased retail price.

Figure4.4 shows the performance of GA while the optimization problem is processed.

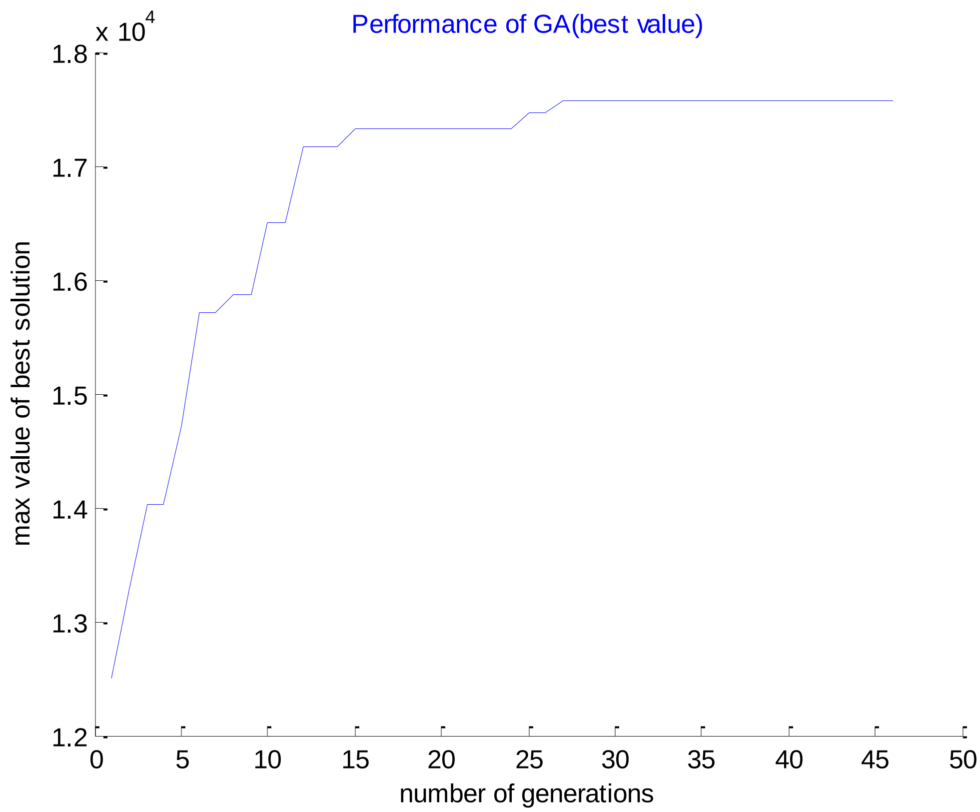

Figure 4.4 Performance of GA

4.1.18 Impact of Interruptible Price on Profit Maximization

Generally, LSEs signs interruptible contracts with end customers which allow LSEs to be secured in case of failing to supply its entire customer load. All they need to do is pay the agreed financial compensation to the customers.

The values of risk factor and retail price are set to the values obtained in Table4.18. Monte- Carlo Simulation is performed by increasing the values of Interruptible price with bidding prices.

Table 4.19 Strategic bidding with various interruptible prices

Interruptible price ($)	Quantity Cleared (MW)	Bidding Price ($)	Expected Profit ($)	Standard Deviation ($)	Net profit ($)	K_{ED} %
[75,35,15]	200	[52,50,48]	6382.1	3807.3	5376.2	59.656
[85,45,25]	400	[56,52,50]	18942	3987	16678	21.049
[95,55,35]	600	[62,60,54]	24598	4172	21757	16.961

From table 4.19 initially, the profit is low because only 200MW were cleared and the LSE has to pay end customers interruptible prices for the un-cleared 400MW. The results from Table4.19 also show that that as interruptible prices to end consumers increases the deviation increases and the net profit of a LSE increases to a point where in there is no interruptible load. Once, there is no interruptible load, the effect of interruptible prices goes off and profit decreases due to high bidding prices which reduces the gap between retail price and bidding price. Thus, LSE will tend to bid high in the market to dispatch more power in order to avoid high interruptible prices to be paid to end customers in case of failing to provide power to end customers.

4.1.19 Optimal Bidding Strategy by GA with Retail and Interruptible Price

GA optimization is applied with interruptible price ranging from $[75, 35, 15] to $[95, 55, 35]. The GA parameters are same as those used in section 4.1.15.

Table4.20 shows the optimal GA values obtained.

Table 4.20 GA optimization with Interruptible Price as a variable member

α	0.90469
Retail price ($)	[139.6,93.344,72.183]
Interruptible price ($)	[83.955,41.16,24.861]
Price ($)	[62.015,59.996,52.034]
Quantity Cleared (MW)	600
Expected Profit ($)	24117
Standard deviation ($)	2280.7
Net profit ($)	21521

Table 4.20 shows the GA optimization with weighting factor, retail price and interruptible price taken into account. The optimum interruptible price obtained is $[83.955, 41.16, and 24.86]. The values of expectation profit and net profit are increased when compared to Table 4.18.

4.1.20 Comparison Analysis

Table 4.21 shows a comparison of three scenarios of bidding strategies from tables 4.16, 4.18 and 4.20. In Scenario1, the retail and interruptible prices are fixed to [100, 80, 55] and [75, 35, 15] respectively. The net profit using Monte-Carlo Simulation method was found to be $6904.9. In scenario2, the retail price was changed to $[138.04, 96.83, 74.37] by the optimization process where as the interruptible price was still fixed to $[75, 35, 15] and the net profit increased to $ 17362. Finally, in scenario3 retail price and interruptible price were changed to $[139.6, 93.344, 72.183] and $[83.955, 41.16, 24.861] respectively by optimization process. The profit in scenario3 increased to $21521.

Table 4.21 Optimal bidding comparison

Factors	Scenario 1	Scenario 2	Scenario 3
Retail price(*a*) ($)	[100,80,55]	[138.04,96.83,74.37]	[139.6,93.344,72.183]
Interruptible price(*b*) ($)	[75,35,15]	[75,35,15]	[83.955,41.16,24.861]
α	0.96699	0.90128	0.90469
Bidding price ($)	[61.789,59.577,57.223]	[62.169,59.143,52.538]	[62.015,59.996,52.034]
Quantity Cleared (MW)	600	600	600
Expected profit ($)	7228.8	19657	24117
Standard deviation ($)	2365.8	2147.2	2280.7
Net profit ($)	6904.9	17362	21521

As the scenario3 involves high profit and low deviation with low risk value it should be preferred for optimal bidding strategy for three blocks bidding per unit time.

4.1.21 Comparison between Single Block Bidding and Three Block Bidding per Unit Time

Table 4.22 gives a complete comparison analysis for optimal bidding strategies for single block bidding (table 4.12) and three block bidding (table 4.21) per unit time in a double-sided competitive electricity markets.

Table 4.22 Comparison Analysis between SBB and TBB per unit time Optimal Bidding Strategies

Factors	Scenario 1		Scenario 2		Scenario 3	
	TBB	SBB	TBB	SBB	TBB	SBB
a ($)	[100,80,55]	100	[138.04,96.83, 74.37]	128.18	[139.6,93.344, 72.183]	139
b ($)	[75,35,15]	75	[75,35,15]	75	[83.955,41.16 ,24.861]	66.52
α	0.96699	0.92914	0.90128	0.97366	0.90469	0.90831
Bidding price ($)	[61.789,59.577, 57.223]	63.545	[62.169,59.143, 52.538]	63.689	[62.015,59.996, 52.034]	60.859
Quantity cleared (MW)	600	600	600	600	600	600
$E(\pi)$ ($)	7228.8	16118	19657	33644	24117	41486
$D(\pi)$ ($)	2365.8	2405.2	2147.2	2366.9	2280.7	2279.7
Net profit ($)	6904.9	14816	17362	32683	21521	37415

Table 4.22 shows that for single block bidding (SBB) per unit time the profits turn out to be maximum in all the scenarios when compared to three block bidding per unit time. The reason for such difference is that in SBB, the retail price at which LSE sells the electric power to the end customer is only one price e.g. $139 in scenario 3 for supplying 600 MW whereas for three block bidding (TBB) per unit time it changes from one block to another block e.g. $[139.6, 93.344, 72.183] in scenario 3 for supplying 600 MW in the order of 200MW for each block. The advantage of SBB optimal bidding strategy is that it can draw high profits but the disadvantage is that if the single price did not clear the market level then the LSE is out of business and should pay the end customers the interruptible prices for unsupplied load as per agreement, which is a loss. Whereas for TBB the profit might be less when compared to SBB but it has the advantage of clearing block quantities in the market. It’s on the LSE to select either of the strategies but before that it should ensure itself of the electricity market process and forecasted load. Researchers of electricity market adopt TBB or more than three block bidding per unit time [64-66].

4.2 Optimal Bidding Strategy with Transmission Constraints

In previous sections of this chapter, the optimal bidding strategy for LSE was developed by neglecting the transmission constraints. This section includes the effect of transmission constraints on the electricity model. An IEEE-30 bus system is considered to study the effect of transmission constraints on the electricity market and bidding strategies of the LSE. The same pricing rule and price settlement process with step-wise price/ quantity biddings are employed. Once the optimal power flow is performed for IEEE-30 bus system, Monte-Carlo Simulation and GA are applied to find the optimal bidding strategy for LSE taking into account the effect of transmission constraints. The optimal bidding strategy is developed using three ways. The first strategy does not include contracts whereas the second strategy includes forward contract only with one generator and finally the third strategy is to contract with more than one generator. The strategies were constructed based on Single Block Bidding (SBB) and Three Block Bidding (TBB) as described in previous sections.

4.2.1 Electricity Market Model

Consider an IEEE-30 bus system with 6 Gencos and 3 LSEs for electricity pool market. One out of the 3 LSEs, suppose LSE at bus 27, is chosen to build optimal bidding strategy.

The participants in the pool market are distributed at different buses as shown in table 4.23 and figure 4.5.

Table 4.23 Market participants in IEEE-30 bus system

Market Participants	**Bus No.**
Genco#1	1
Genco#2	2
Genco#3	22
Genco#4	27
Genco#5	23
Genco#6	13
LSE#1	7
LSE#2	15
LSE#3	**27**

LSE at bus no. 27 is chosen to build the optimal bidding strategy.

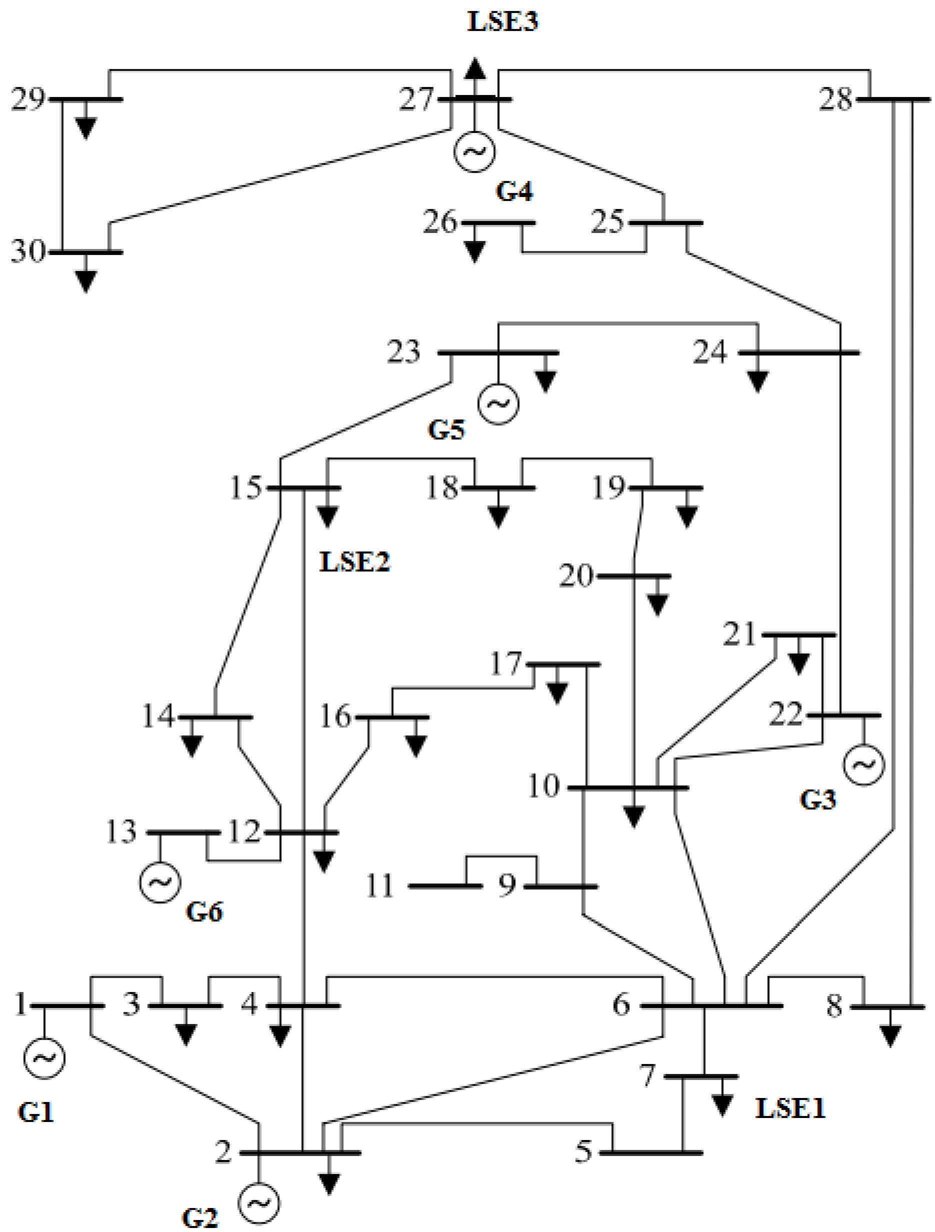

Figure 4.5 Single Line Diagram of the IEEE-30 Bus test system

In general, cost function of a generator is given by the following polynomial

$$F(C) = aP^2 + bP + c \qquad (4.2)$$

Table 4.24 shows the generator cost functions of each generator.

Table 4.24 Generator Cost Functions

Gen	Block1			Block2			Block3		
	a $(\frac{\$}{MWh^2})$	B $(\frac{\$}{MWh})$	c($)	a $(\frac{\$}{MWh^2})$	b $(\frac{\$}{MWh})$	c($)	a $(\frac{\$}{MWh^2})$	b $(\frac{\$}{MWh})$	c($)
G1	0.02	21.5	0	0.02	49	0	0.02	59	0
G2	0.02	20.5	0	0.02	39	0	0.02	69	0
G3	0.02	19.5	0	0.02	47	0	0.02	59	0
G4	0.02	22.5	0	0.02	41	0	0.02	79	0
G5	0.02	23.5	0	0.02	45	0	0.02	74	0
G6	0.09	85	0	0.09	90	0	0.09	95	0

Each Genco has the maximum capacity of 60 MW while the forecasted load of each LSE is 30 MW. Each generation company can bid at most Ig blocks for each period; the block price must be non-decreasing with the increase of the block number. Each LSE can bid at most Id blocks for each period, the block price must decrease with the increase of the block number.

Suppose each market participant is allowed to bid at most 3 blocks (Ig=3 and Id=3).

Table 4.25 shows the estimated parameters of generators. Table 4.25 also shows that the bidding prices for Gencos are increasing from one block to the another block, i.e. it is $22 for Genco 1 during block 1 then $50 during block 2 and finally $60 during block 3. The other Gencos also follow the same increasing block prices for their supplied capacity.

Table 4.25 Offering Parameters of Gencos

Genco	Block1		Block2		Block3		Variance	
	MW	$	MW	$	MW	$	MW	$
1	12	22	24	50	24	60	5.5	2.5
2	12	21	24	40	24	70	5.5	2.5
3	12	23	24	42	24	80	5.5	2.5
4	12	85	24	90	24	95	5.5	2.5
5	12	24	24	46	24	75	5.5	2.5
6	12	20	24	48	24	60	5.5	2.5

Table 4.26 shows the estimated bidding parameters of LSEs. Table 4.26 also shows that the bidding prices for LSEs are decreasing from one block to the another block, i.e. it is $100 for LSE 1 during block 1 then $70 during block 2 and finally $60 during block 3. The other LSEs also follow the same decreasing block prices for their supplied capacity.

Table 4.26 Bidding Parameters of LSEs

LSE	Block1		Block2		Block3		Variance	
	MW	$	MW	$	MW	$	MW	$
1	10	100	10	70	10	60	5.5	2.5
2	10	100	10	50	10	20	5.5	2.5

For this model, at first, OPF is run without transmission constraints and the expectation profit, standard deviation and net profit are calculated in the same manner as in chapter 5 using Monte-Carlo Simulation. Then OPF is run with transmission constraints[72]. The nodal prices and quantity cleared at different buses are examined. Finally, optimal bidding strategy was developed for LSE 3 using SBB and TBB. This optimal bidding strategy was developed including and excluding forward contracts.

The bus data, line data and generation data for IEEE-30 bus system with 6 generators is mentioned in Appendix A of this thesis. At first, OPF program is performed without transmission constraints. The results of OPF without transmission constraints are given in Appendix B. This flow determines the nodal prices at different buses and the load cleared at the bus. As shown in figure 4.6, without any transmission line limits, 30 MW of load is cleared at bus 27. Generator at bus 27 does not produce any MW since it is the costliest generator. Thus, without transmission constraints, the other generators which are less costly than generator at bus 27 transmit MWs to the load at bus 27. The nodal price is found to be $79.134 at bus 27. The various generations of generators and line flows are shown in the OPF bus data and OPF branch data without transmission constraints in Appendix B.

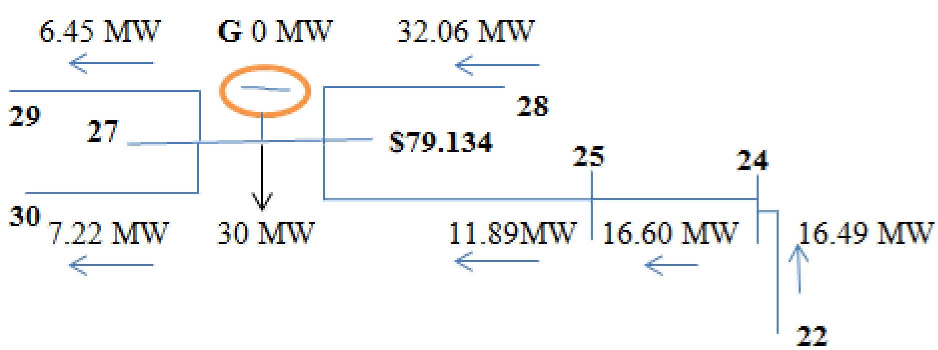

Figure 4.6 Flow of the lines to bus 27 without transmission constraints

The different bidding strategies adopted by LSE at bus 27 with retail price $150 and interruptible price $110 are shown in Table 4.27.

Table 4.27 Bidding Strategy without transmission constraints

Bidding Prices ($)	Quantity Cleared (MW)	Expected Profit ($)	Standard Deviation ($)
80	30	2286.7	6451.3
90	30	1970.1	6021.9
100	30	1654.4	5709.4

LSE 3 should bid higher than the nodal price at bus 27 to clear 30 MW of load. Table 4.27 shows that if LSE bids higher than nodal price, it clears 30 MW but further increase in bidding price reduce the gap between bidding price and retail price. This reduction in gap reduces its expected profit.

The optimal power flow program for the electricity market model with transmission constraints is performed. The power flow limits on each line of an IEEE-30 bus system are shown in the line data for an IEEE-30 bus system in Appendix A. The results of OPF with transmission constraints are given in Appendix C. Generator at bus 27, is an expensive generator for producing power. When there were no transmission constraints, generator at bus 27 does not produce because low cost generators were able to transmit power to bus 27. As shown in figure 4.7, due to transmission limits on the lines (line 22 to 24 and line 24 to 25) of the network, the flow to bus 27 is limited. Thus, the low cost generators are unable to transmit power to bus 27. The remaining MWs are produced by the generator at bus 27. This generator produces 5.04 MW and thus the nodal price at this bus is set by this generator and is found to be $ 85.906. The various generations of generators and line flows are shown in the OPF bus data and OPF branch data with transmission constraints in Appendix C.

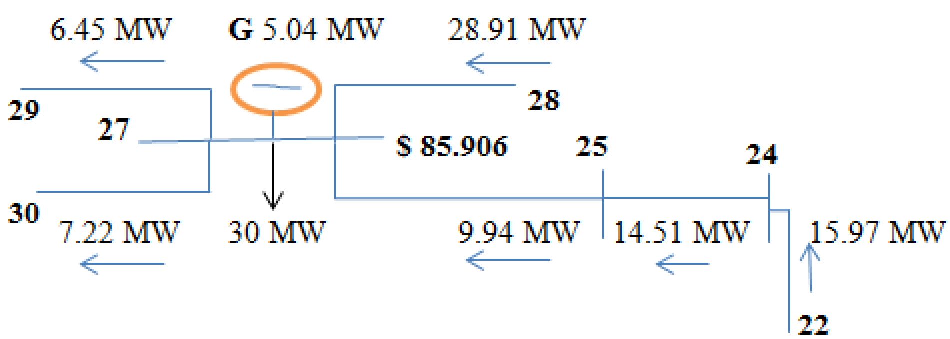

Figure 4.7 Flow of the lines to bus 27 with transmission constraints

The thesis develops strategic bidding for LSE at bus 27 using SBB and TBB per unit time with three cases, i.e.

1. When LSE at bus 27 does not undertake bilateral contract.
2. When LSE at bus 27 undertake a contract with one of the available generators
3. When LSE at bus 27 undertake contracts with more than one available generators

Single Bidding Block per Unit Time

The LSE at bus 27 will bid only a single price for the all the blocks to clear 30MW.

No Bilateral Contract

Considering SBB per unit time and does not involve any contracts, the bidding strategies of LSE at bus 27 can be constructed step by step as in the chapter 5.

4.2.2 Profits with Different Bidding Strategies with Different Weighting Factors

Initially, the retail price is set to \$150 and the interruptible price is set to \$110. Maximum number of random sampling is set as $T = 5000$. The bidding strategies of rivals are described according to equations 3.14 and 3.16. Risk factor is increased from 0.3 to 0.9 and Monte-Carlo Simulation is used for the calculation of expectation profit and standard deviation. The impact of different bidding strategies on $E(\pi)$and $D(\pi)$ of the LSE X is shown in Table 4.28.

Table 4.28 Profits with Different Bidding Strategies

α	Bidding Prices (\$)	Quantity Cleared (MW)	Expected Profit (\$)	Standard Deviation (\$)	Net Profit (\$)
0.3	80	0	-3089.7	6338.5	-5363.8
0.6	90	30	1972.4	5951.5	1197.2
0.9	100	30	1656.2	5686	921.94

It is observed from the table 4.28; if the bidding price is less than the nodal price then LSE will not clear any quantity and is out of business with loss. If it's bidding price is greater than the nodal price then it clear all the quantity and the profit increases. Once the load is cleared the high bidding prices will reduce the profit because the gap between bidding price and retail price reduces. Also it shows that LSE should prefer high weighting/risk factor to maximize profit.

4.2.3 Optimal Bidding Strategy with Weighting Factor

The GA optimization is applied to get the optimal bidding strategy among the results obtained from Monte-Carlo results of all bidding strategies. The parameters associated with GA are specified as Population is 100, mutation probability is 0.1, crossover probability is 0.8 and maximum permitted number of iterations is 100. GA optimization for risk factor ranging from 0 to 1 is shown in Table 4.29.

Table 4.29 Optimal Bidding Strategy with Weighting Factor

α	0.99885
Bidding Price ($)	99.662
Cleared Quantity (MW)	30
Expected Profit ($)	1665.4
Standard Deviation ($)	2133.7
Net Profit ($)	1657

4.2.4 Impact of Retail Price on Profit Maximization

Retail price is the price at which LSEs would sell the power to the end customers. Thus, it is a very important factor for a LSE to maximize its profit. LSE X should choose retail price such that it should neither be too high such that end customers look out for other LSEs making LSE X out of business nor the retail price should be too low such that it causes LSE X to incur a loss. Using the results obtained from optimal bidding strategy for weighting factor, i.e. Table4.29; weighting factor (also known as risk factor) is fixed to 0.99885 and interruptible price is fixed to \$110. The values of retail prices are increased from \$150 to \$180 with increasing bidding prices. Results obtained from Monte-Carlo Simulation are shown in Table 4.30.

Table 4.30 Impact of Retail Price on Profit Maximization

Retail Price (\$)	Quantity Cleared (MW)	Bidding Price (\$)	Expected Profit (\$)	Standard Deviation (\$)	Net profit (\$)
150	0	80	-3040.4	5409.9	-3045.4
160	30	90	2286.7	6387.6	2276.7
180	30	100	2598.2	6687.1	2587.6

Table 4.30 shows that when the bidding price is less than the nodal price then LSE will not clear any quantity and is out of business with loss. Table 4.30 also shows as retail price increases the profit of the LSE increases and also increases the deviation. . The increase in profit is due to increased gap between bidding price and retail price. The high

retail prices will encourage LSE to bid high in the market to dispatch more power. The increasing of retail price may cause the consumers to choose the other LSEs which offers low retail price.

4.2.5 The Optimal Bidding Strategy with Retail Prices

In order to decide whether the increased retail price which gives the LSE a large profit is optimal or not, GA optimization is applied with retail price ranging from \$150 to\$180 with same GA parameters used in section 4.2.3. The results obtained for different parameters are shown in Table4.31.

Table 4.31 Optimal Bidding Strategy with Retail Prices

α	0.98235
Retail price (\$)	178.77
Bidding Price (\$)	88.163
Quantity Cleared (MW)	30
Expected Profit (\$)	2932.1
Standard deviation (\$)	2282.4
Net profit (\$)	2755.6

4.2.6 Impact of Interruptible Price on Profit Maximization

The values of risk factor and retail price are fixed to the values obtained in Table 4.31. Monte- Carlo Simulation is performed by increasing the values of Interruptible price.

Table 4.32 Impact of Interruptible Price on Profit Maximization

Interruptible price ($)	Quantity Cleared (MW)	Bidding Price ($)	Expected Profit ($)	Standard Deviation ($)	Net profit ($)
90	0	80	-2472.7	6649	-2546.4
100	30	90	2860.6	6718.5	2691.6
110	30	100	2531.3	6977.5	2381.1

Table 4.32 shows that, when the bidding price is lower than nodal price at bus 27, the quantity cleared is 0 MW and LSE at bus 27 should pay end customers an interruptible price of $110. Thus, in this case profit is negative. Also it can be observed form Table 4.32 that as bidding prices increases there is no effect of interruptible prices because the required 30 MW are fully cleared. In general, high interruptible prices force LSE to bid higher to dispatch the required quantity.

4.2.7 Optimal Bidding Strategy by GA with Retail and Interruptible Price

GA optimization is applied with interruptible price ranging from \$90 to \$110 with same GA parameters used in section 4.2.3. Table 4.33 shows the optimal GA values obtained.

Table 4.33 Optimal Bidding Strategy by GA with Retail and Interruptible Price

α	0.97481
Retail price (\$)	179
Interruptible price (\$)	92.442
Bidding Price (\$)	88.02
Quantity Cleared (MW)	30
Expected Profit (\$)	2921.6
Standard deviation (\$)	2407.5
Net profit (\$)	2684.8

4.2.8 Comparison Analysis

Table 4.34 shows the comparison of three scenarios of bidding strategies discussed in tables 4.29, 4.31 and 4.33. In Scenario1, the retail and interruptible prices are fixed to $150 and $110 respectively. The net profit using Monte-Carlo Simulation method was found to be $1657. In scenario2, the retail price was found to be $178.77 by the optimization process where as the interruptible price was still fixed to $110 and the net profit increased $ 2755.6. Finally, in scenario3 retail price and interruptible price were found to be $179 and $92.442 respectively by optimization process. The profit in scenario3 increased to $2527.2.

Table 4.34 Comparison Analysis

Factors	Scenario 1	Scenario 2	Scenario 3
Retail price ($)	150	178.77	179
Interruptible price($)	110	110	92.442
α	0.99885	0.98235	0.97481
Bidding price ($)	99.662	88.163	88.02
Quantity Cleared (MW)	30	30	30
Expected profit ($)	1665.4	2932.1	2933.4
Standard deviation ($)	2133.7	2282.4	2207.5
Net profit ($)	1657	2755.6	2527.2

As the scenario3 involves high profit (less than scenario 2 with high risk) and low deviation with low risk value it should be preferred for optimal bidding strategy for single block bidding per unit time.

Bilateral Contract with One of the Available Generators

The results of different variations in the prices of LSE at bus 27 due to variations in the production of generators at different buses are shown in table 4.35. Generators at bus 13 and at bus 23 were selected for optimal bidding strategy for LSE at bus 27. The reason for selecting only generators at bus 13 and at bus 23 is that the absence of these generators makes the generator at bus 27 to produce more MW which results in high prices (i.e., $93.813 if generator at bus 13 produces only 12 MW and $94.256 if the generator at bus 27 produces only 12 MW) as shown in table 4.35. So, in order to avoid such high prices, LSE at bus 27 may consider signing a contract with generators at bus 13 and at bus 23. As in case2, LSE at bus 27 has to undertake contract only with one generator, it would be generator at bus 13 since it provides more MW (i.e. 25 MW) to LSE at low prices when compared to generator at bus 23. In case3, LSE is allowed to contract with more than one generators available i.e. generators at bus 13 and at bus 23. The comparative results are shown in section 4.36. The contract settlements for these two parties are shown in Appendix D.

Table 4.35 Variations in prices at bus 27 due to variations in production at different generator buses

Generator	G1 (MW)	G2 (MW)	G13 (MW)	G22 (MW)	G23 (MW)	G27 (MW)	Load at bus 27 (MW)	Nodal Price at bus 27 ($)
G1	12	60	60	59.3	46.18	18.58	30	91.185
	36	60	60	38.9	50.34	11.29	30	87.033
	60	57.14	60	36	39.13	5.04	30	85.906
G2	60	12	60	59.4	46.17	18.74	30	91.213
	60	36	60	39	50.32	11.39	30	87.05
	58.01	60	60	36	37.66	5.62	30	86.012
G13	60	60	12	55.68	36.08	33.18	30	93.813
	60	60	36	45.54	46.34	9.37	30	86.686
	60	57.14	60	36	39.13	5.04	30	85.916
G22	60	60	60	12	52.28	12.83	30	90.150
	60	57.14	60	36	39.13	5.04	30	85.906
	37.22	36	59.29	60	45.47	18.20	30	91.117
G23	60	56.26	57.94	36	12	35.64	30	94.256
	60	58.59	60	36	36	6.69	30	86.205
G27	60	52.83	60	36	36	12	30	87.159
	51.39	36	60	36	36	36	30	95.00
	36	36	50.85	36	36	60	30	99.89

All generations are in MW and prices are in $.

Consider that LSE 3 would sign a contract with generator at bus 13 for the supply of 25 MW at bus27. The contract price is a compromise between these two parties and an average price of $78 is always the best contract price. LSE 3 also owns the Financial Transmission Rights (FTRs) between bus 13 and bus 27 at a price equal to difference in nodal prices of bus 13 and bus 27 i.e., $15.789. Contract details are shown in Appendix D. The bidding strategy for LSE at bus 27 with a single contract is obtained step by step from following sections.

4.2.9 Profits with Different Bidding Strategies

The impact of different bidding strategies on $E(\pi)$and $D(\pi)$ of the LSE X is shown in Table 4.36

Table 4.36 Profits with different bidding strategies

Bidding Prices ($)	**Quantity Cleared (MW)**	**Expected Profit ($)**	**Standard Deviation ($)**
80	25	1665.3	8320.1
90	30	2357.9	8242.3
100	30	2309.5	8223.7

Table 4.36 shows that at least a quantity of 25 MW will be cleared at bus 27 even though the price is less than nodal price at bus 27. This is because of contract between generator at bus 13 and LSE at bus 27. The remaining will be cleared by LSE using its bidding strategies where its bidding prices are greater than nodal prices. In this case, LSE will not be exposed to any kind of loss.

4.2.10 Impact of Different Weighting Factor on Bidding Strategies

The impact of different Weighting or risk factor on bidding strategies of the LSE X is shown in Table 4.37

Table 4.37 Impact of Different Weighting Factor on Bidding Strategies

α	Bidding Prices ($)	Quantity Cleared (MW)	Expected Profit ($)	Standard Deviation ($)	Net Profit ($)
0.3	80	25	1665.3	8320.1	1665.3
0.6	90	30	2357.9	8242.3	1882.2
0.9	100	30	2309.5	8223.7	1811.76

Table4.37 shows that increasing risk factor, with increasing bidding prices, increases the net profit of LSE. The contract of 25 MW always results in profit even though the bidding price is less than the nodal price. For the LSE, to clear remaining 5 MW from the market, it should bid high with high factor of risk.

4.2.11 Optimal Bidding Strategy with weighting Factor

GA optimization with weighting factor ranging from 0 to 1 is applied to get optimum value for weighting factor. The parameters used for GA are the same used before. The optimized solution of GA is shown in Table 4.38

Table 4.38 Optimal Bidding Strategy with Weighting Factor

α	0.99171
Bidding price ($)	98.746
Quantity Cleared (MW)	30
Expected Profit ($)	2372.0
Standard Deviation ($)	2026.7
Net Profit ($)	2284.0

4.2.12 Impact of Retail Price on Profit Maximization

Using the results obtained from optimal bidding strategy for weighting factor, i.e. Table4.38; risk factor is fixed to 0.99171 and interruptible price is set to $110. The values of retail prices are increased from $150 to $180 with bidding prices. The results obtained from Monte-Carlo Simulation are shown in Table4.39

Table 4.39 Impact of Retail Price on Profit Maximization

Retail Price ($)	Quantity (MW)	Bidding Price ($)	Expected Profit ($)	Standard Deviation ($)	Net profit ($)
150	25	80	1571.1	8389.5	1571.1
160	30	90	2712.4	8648.8	2595.0
180	30	100	3285.3	8846.7	3188.3

Table4.39 shows as retail price increases the profit of the LSE increases and also increases the deviation. The increase in profit is due to increased gap between bidding price and retail price. The high retail prices will encourage LSE to bid high in the market to dispatch more power. The increasing of retail price may cause the consumers to choose the other LSEs which offers low retail price.

4.2.13 The Optimal Bidding Strategy with Retail Prices

GA optimization with retail prices ranging from 150 to 180 is applied to get optimum value for retail price. The parameters used for GA are the same used before. The optimized solution of GA is shown in Table 4.40.

Table 4.40 Optimal Bidding Strategy with Retail Prices

α	0.98735
Retail price ($)	179.41
Bidding Price ($)	87.263
Quantity Cleared (MW)	30
Expected Profit ($)	3291.5
Standard deviation ($)	2235.9
Net profit ($)	3132.0

4.2.14 Impact of Interruptible Price on Profit Maximization

The values of risk factor and retail price are set to the values obtained in Table4.40. By increasing the values of Interruptible price the Monte- Carlo Simulation is performed.

Table 4.41 Impact of Interruptible Price on Profit Maximization

Interruptible price ($)	Quantity (MW)	Bidding Price ($)	Expected Profit ($)	Standard Deviation ($)	Net profit ($)
90	25	80	2405.1	8665	2405.1
100	30	90	3322.7	8866.6	3127.9
110	30	100	3253.6	8639.3	3103.1

Table 4.41 shows that as bidding prices increases there is no effect of interruptible prices because the required 30 MW are cleared. In general, high interruptible prices force LSE to bid higher to dispatch the required quantity.

4.2.15 Optimal Bidding Strategy by GA with Retail and Interruptible Price

GA optimization with interruptible price ranging from 90 to 110 is applied to get optimum value for interruptible price. The parameters used for GA are the same used before. The optimized solution of GA is shown in Table 4.42

Table 4.42 Optimal Bidding Strategy by GA with Retail and Interruptible Price

α	0.957
Retail price ($)	179.22
Interruptible price ($)	93.989
Bidding Price ($)	87.76
Quantity Cleared (MW)	30
Expected Profit ($)	3311.3
Standard deviation ($)	2207.5
Net profit ($)	2789.2

4.2.16 Comparison Analysis

Table 4.43 shows the comparison of three scenarios discussed in tables 4.38, 4.40 and 4.42 three scenarios can be studied as shown in table 4.19. In Scenario1, the retail and interruptible prices are fixed to $150 and $110 respectively. The net profit using Monte-Carlo Simulation method was found to be $2284.0. In scenario2, the retail price was changed to $179.41 by the optimization process where as the interruptible price was still fixed to $110 and the net profit increased to $ 3132.0. Finally, in scenario3 retail price and interruptible price were found to be $179.22 and $93.989 respectively by optimization process. The profit in scenario3 increased to $2789.2.

Table 4.43 Comparison Analysis

Factors	Scenario 1	Scenario 2	Scenario 3
Retail price ($)	150	179.41	179.22
Interruptible price ($)	110	110	93.989
α	0.99171	0.98735	0.957
Bidding price ($)	98.746	87.263	87.76
Quantity Cleared ($)	30	30	30
Expected profit ($)	2372.0	3291.5	3311.3
Standard deviation ($)	2026.7	2235.9	2207.5
Net profit ($)	2284.0	3132.0	2789.2

As the scenario3 involves high profit (less than scenario 2 with high risk) and low deviation with low risk value it should be preferred for optimal bidding strategy for single block bidding per unit time.

4.2.17 Comparison of SBB with and without Contract

Table 4.44 shows comparison of SBB with and without contract from tables 4.43 and 4.34.

Table 4.44 Comparison of SBB with and without contract

Factors	Scenario 1		Scenario 2		Scenario 3	
	SBB with Contract	SBB without Contract	SBB with Contract	SBB without Contract	SBB with Contract	SBB without Contract
Retail price	150	150	179.41	178.77	179.22	179
Interruptible price	110	110	110	110	93.989	92.442
α	0.99171	0.99885	0.98735	0.98235	0.957	0.97481
Bidding price	98.746	99.662	87.263	88.163	87.76	88.02
Expected profit	2372.0	1665.4	3291.5	2932.1	3311.3	2933.4
Standard deviation	2026.7	2133.7	2235.9	2282.4	2407.5	2207.5
Net profit	2284.0	1657	3132.0	2755.6	2789.2	2527.2

It is observed from table 4.44 that the profit obtained by LSE 3 at bus 27 while constructing optimal bidding strategy with contractual tools is more when compared to optimal bidding strategy without contracts. Hence LSEs at buses should undertake contracts in order to avoid price fluctuations at nodes and also to maximize their profit

Bilateral Contracts with More than One Available Generators

When LSE at bus 27 undertakes bilateral trading of 26 MW with generator at bus 13 for $78 and a trade of 4 MW with generator at 23 for $82 then the optimal bidding strategy using SBB for LSE at 27 is shown in table 4.45. The settlement of contracts is shown in Appendix D. In scenario1, retail price and interruptible price are fixed to $150 and $110 respectively. The net profit in scenario 1 was found to be $2124.2. In scenario2, the optimal retail price was found to be $179.41 and interruptible price is fixed to $110 and net profit was found to be $ 29654. In scenario3, the optimal retail and interruptible prices were found to be $179.22 and $ 93.989 with a net profit of $2775.5.

Table 4.45 optimal bidding strategy using forward contracts with two generators

Factors	Scenario 1	Scenario 2	Scenario 3
Retail price ($)	150	179.41	179.22
Interruptible price ($)	110	110	93.989
α	0.99171	0.98735	0.957
Quantity Cleared (MW)	30	30	30
Expected profit ($)	2160.0	3291.5	3036.6
Standard deviation ($)	2160.3	2090.5	2070.2
Net profit ($)	2124.2	29654	2775.5

The table 4.45 shows that the profit obtained from contracting with more than one available generator increases the profit of LSE at bus 27 when compared to no contract and contract with only one out of available generators analysis. This increase in profit is due to no high bidding prices involved and low price contracts provided by the generators.

Three Block Bidding per Unit Time

The LSE at bus 27 will bid different prices for each block to clear 30 MW.

No Bilateral Contract

Considering TBB per unit time and does not involving any contracts, the bidding strategies of LSE at bus 27 can be constructed step by step in same way as done for SBB.

Without transmission constraints Nodal Price at bus 27 was found to be $79.134.

4.2.18 Profits with Different Bidding Strategies

Initially, the retail price is set to $[150,120, 100] and the interruptible price is set to $[110, 85, 70]. Maximum number of random samples are set to $T = 5000$ and the bidding strategies of rivals are described according to equations 3.14 and 3.16 [64-66].The expectation profit and standard deviation for different bidding strategies by LSE at bus 27 when transmission constraints are neglected are given by the table 4.46.

Table 4.46 Profits with Different Bidding Strategies

Bidding Prices ($)	Quantity Cleared (MW)	Expected Profit ($)	Standard Deviation ($)
[100,60,50]	10	-904	5082.7
[100,80,70]	20	316.6	4580
[100,90,80]	30	1098.3	4402
[120,90,80]	30	888.6	4179

The quantity is cleared depending upon the bidding price per block. Table 4.26 shows initially the profit of LSE is negative because the quantity cleared when bidding with

$[100, 60, 50] is only 10 MW. The LSE has to pay the end customers the interruptible price for the un-cleared quantity i.e. 20 MW according interruptible contracts. Table 4.26 also shows that as the bidding prices increases the profit of LSE increases. Once the total quantity is cleared interruptible load will have no effect on the profit of LSE. If the bidding prices are further increased then the profit of LSE will decrease since the gap between retail and bidding price decreases.

Nodal price at bus 27 with transmission constraints was found to be $85.906.

4.2.19 Profits with Different Bidding Strategies and Weighting Factors

The expectation profit and standard deviation for different bidding strategies with different weighting factors for LSE at bus 27 when transmission constraints are taken into account are given by the table 4.47.

Table 4.47 Profits with Different Bidding Strategies

α	**Bidding Prices ($)**	**Quantity Cleared (MW)**	**Expected Profit ($)**	**Standard Deviation ($)**	**Net Profit ($)**
0.3	[100,60,50]	10	-902.6	5112.5	-1323.6
0.6	[100,90,80]	20	206.1	4395.6	-254
0.9	[120,100,90]	30	678.4	3932.6	217.3

Negative values of expected profit and net profit in table 4.47 show that when bidding lower price at lower factor of risk will make the LSE at bus 27 undergo loss since the cleared quantity is only 10MW and risk factor is very low. Table 4.47 also shows that, when LSE increases its factor of risk, with increasing bidding prices, the profit increases. Thus, LSEs when bidding should always prefer to bid high with high factor of risk in order to maximize their net profit.

4.2.20 Optimal Bidding Strategy with Weighting Factor

The GA optimization is applied to get the optimal bidding strategy among the results obtained from Monte-Carlo results of all bidding strategies. The parameters associated with GA are specified as Population is 100, mutation probability is 0.1, crossover probability is 0.8 and maximum permitted number of iterations is 100. GA optimization for risk factor ranging from 0 to 1 is shown in Table 4.48.

Table 4.48 Optimal Bidding Strategy with Weighting Factor

α	0.99539
Bidding price ($)	[117.53, 95.249,88.879]
Quantity Cleared (MW)	30
Expected Profit ($)	747.05
Standard Deviation ($)	2450.8
Net Profit ($)	724.87

4.2.21 Impact of Retail Price on Profit Maximization

Using the results obtained from optimal bidding strategy for weighting factor, i.e. Table 4.48; risk factor is fixed to 0.99539 and interruptible price is fixed to $[110, 90, 75]. The values of retail prices are increased from $[150,120,100] to $[180,160,140] with bidding prices. Results obtained from Monte-Carlo Simulation are shown in Table 4.49

Table 4.49 Impact of Retail Price on Profit Maximization

Retail Price ($)	Quantity (MW)	Bidding Price ($)	Expected Profit ($)	Standard Deviation ($)	Net profit ($)
[150,120,100]	10	[100,60,50]	-904.17	5098.1	-923.51
[160,140,120]	20	[100,90,80]	531.84	5083.6	505.95
[180,160,140]	30	[120,100,90]	1833.3	5181.1	1800.9

The reason for negative profit is same as mentioned in section 4.2.19. Table4.49 shows as retail price increases the profit of the LSE increases. This encourages LSE to bid high with high retail price in order to maximize the overall profit. The increasing of retail price may cause the consumers to choose the other LSEs which offers low retail price.

4.2.22 Optimal Bidding Strategy with Retail Prices

The GA optimization is applied to get the optimal bidding strategy among the results obtained from Monte-Carlo results of all bidding strategies. The parameters associated with GA are specified as Population is 100, mutation probability is 0.1, crossover probability is 0.8 and maximum permitted number of iterations is 100. GA optimization for retail price ranging from [150,120,100] to [180,160,140] is shown in Table 4.50.

Table 4.50 Optimal Bidding Strategy with Retail Prices

α	0.97178
Retail price ($)	[177.07, 153.37,132.31]
Bidding Price ($)	[109.84, 94.991,88.041]
Quantity Cleared (MW)	30
Expected Profit ($)	1700
Standard deviation ($)	2133.2
Net profit ($)	1504

4.2.23 Impact of Interruptible Price on Profit Maximization

The values of risk factor and retail price are fixed to the values obtained in Table 4.50. By increasing the values of Interruptible price with bidding price Monte- Carlo Simulation is applied and the results are shown in table 4.51.

Table 4.51 Impact of Interruptible Price on Profit Maximization

Interruptible price ($)	Quantity (MW)	Bidding Price ($)	Expected Profit ($)	Standard Deviation ($)	Net profit ($)
[90,65,50]	10	[100,60,50]	-215.05	5437.2	-362.42
[100,75,60]	20	[100,90,80]	942.92	5221.1	768.97
[110,85,70]	30	[120,100,90]	1650.8	5009.9	1462.8

It can be observed form Table4.51 that as interruptible prices to end consumers decrease the net profit of a LSE. Also it can be observed form Table 4.51 that as bidding prices increases there is no effect of interruptible prices because the required 30 MW are cleared which means there is no interruptible load. In general, high interruptible prices tend LSE to bid higher to dispatch the required quantity.

4.2.24 Optimal Bidding Strategy by GA with Retail and Interruptible Price

The GA optimization is applied to get the optimal interruptible price. The GA parameters are same as used before. Table 4.52 shows the optimal value of interruptible price.

Table 4.52 Optimal Bidding Strategy by GA with Retail and Interruptible Price

α	0.97481
Retail price ($)	[178.04,158.14,133.79]
Interruptible price ($)	[88.714,74.476,59.116]
Bidding Price ($)	[117.7, 92.422,88.459]
Quantity Cleared (MW)	30
Expected Profit ($)	1827.9
Standard deviation ($)	2107.5
Net profit ($)	1662.8

4.2.25 Comparison Analysis

Table 4.53 shows the comparison of three scenarios discussed in tables 4.48, 4.50 and 4.52. In Scenario1, the retail and interruptible prices are fixed to $[150, 100, 75] and $[110, 85, 70] respectively. The net profit using Monte-Carlo Simulation method was found to be 724.87. In scenario2, the retail price was changed to $[177.07, 153.37, 132.31] by the optimization process where as the interruptible price was still fixed to $[110, 85, 70] and the net profit increased to $1504. Finally, in scenario3 retail price and interruptible price were changed to $[178.04, 158.14, 133.79] and $[88.714, 74.476, 59.116] respectively by optimization process. The profit in scenario3 increased to $1662.8.

Table 4.53 Comparison Analysis

Factors	Scenario 1	Scenario 2	Scenario 3
Retail price ($)	[150,120,100]	[177.07 153.37,132.31]	[178.04,158.14,133.79]
Interruptible price ($)	[110,85,70]	[110,85,70]	[88.714,74.476,59.116]
α	0.99539	0.97178	0.97481
Bidding price ($)	[117.53,95.249,88.879]	[109.84,94.991,88.041]	[117.7, 92.422,88.459]
Expected profit ($)	747.05	1700	1827.9
Standard deviation ($)	2450.8	2133.2	2107.5
Net profit ($)	724.87	1504	1662.8

As the scenario3 involves high profit and low deviation with low risk value it should be preferred for optimal bidding strategy for three blocks bidding per unit time.

Bilateral Contract with One of the Available Generators

Consider that LSE 3 would sign a contract with generator at bus 13 for the supply of 25 MW at bus27. The contract price is a compromise between these two parties and an average price of $78 is always the best contract price. LSE 3 also owns the Financial Transmission Rights (FTRs) between bus 13 and bus 27 at a price equal to difference in nodal prices of bus 13 and bus 27 i.e., $15.789. Contract details are shown in Appendix D. The bidding strategy for LSE at bus 27 with a single contract is obtained step by step from following sections.

4.2.26 Profits with Different Bidding Strategies

Monte-Carlo Simulation is performed to find the profits with different bidding strategies with weighting factor ranging from 0.3 to 0.9 as shown in table 4.54.

Table 4.54 Profits with Different Bidding Strategies

α	Bidding Prices ($)	Quantity Cleared (MW)	Expected Profit ($)	Standard Deviation ($)
0.3	[100,60,50]	28	1235.3	5155.5
0.6	[100,90,80]	29	1321.1	4400.6
0.9	[100,95,90]	30	1387.7	4297.0

Table 4.54 shows that at least a quantity of 25MW will be cleared at bus 27 even though the price is less than nodal price at bus 27 by forward contracts. The remaining will be

cleared by LSE using its bidding strategies where its bidding prices are greater than nodal prices. In this case, LSE will not be exposed to any kind of loss.

4.2.27 Optimal Bidding Strategy with Weighting Factor

GA optimization is performed with weighting factor ranging from 0 to 1. The parameters used for GA are the same used before.

Table 4.55 Optimal Bidding Strategy with Weighting Factor

α	0.99911
Bidding price ($)	[118.8, 97.286,88.411]
Quantity Cleared (MW)	30
Expected Profit ($)	1289.9
Standard Deviation ($)	2452.2
Net Profit ($)	1285.2

4.2.28 Impact of Retail Price on Profit Maximization

Using the results obtained from optimal bidding strategy for weighting factor, i.e. Table 4.55; risk factor to is fixed to 0.99911. The values of retail prices are increased from $[150,120,100] to $1[180,160,140] with bidding prices. Results obtained from Monte-Carlo Simulation are shown in Table 4.56.

Table 4.56 Impact of Retail Price on Profit Maximization

Retail Price ($)	Quantity (MW)	Bidding Price ($)	Expected Profit ($)	Standard Deviation ($)	Net profit ($)
[150,120,100]	28	[100,60,50]	1236.1	5081.7	1230.5
[160,140,120]	29	[100,90,80]	1825.9	5048.9	1819.8
[180,160,140]	30	[100,95,90]	2541.7	5594.9	2534.4

Table4.56 shows as retail price increases the profit of the LSE increases. This encourages LSE to bid high with high retail price in order to maximize the overall profit. The increasing of retail price may cause the consumers to choose the other LSEs which offers low retail price.

4.2.29 The Optimal Bidding Strategy with Retail Price

GA optimization is performed with retail prices ranging from [150,120,100] to [180,160,140]. The parameters used for GA are the same used before.

Table 4.57 Optimal Bidding Strategy with Retail Prices

α	0.99321
Retail price ($)	[179.93,143.29,139.91]
Bidding Price ($)	[109.85,97.142,88.841]
Cleared Quantity (MW)	30
Expected Profit ($)	2312.6
Standard deviation ($)	2439.1
Net profit ($)	2261.2

4.2.30 Impact of Interruptible Price on Profit Maximization

The values of risk factor and retail price are set to the values obtained in Table 4.57. Monte- Carlo Simulation is applied by increasing the values of Interruptible price along with bidding price. Table 4.58 shows the results obtained.

Table 4.58 Impact of Interruptible Price on Profit Maximization

Interruptible price ($)	Quantity (MW)	Bidding Price ($)	Expected Profit ($)	Standard Deviation ($)	Net profit ($)
[90,65,50]	28	[100,60,50]	2161.2	5397.5	2109.8
[100,75,60]	29	[100,90,80]	2253.9	5115.4	2203.8
[110,85,70]	30	[100,95,90]	2367	5254.4	2315.2

Table 4.58 shows that as bidding prices increase the effect of interruptible prices decrease because the required 30 MW are cleared which means there is no interruptible load. In general, high interruptible prices force LSE to bid higher to dispatch the required quantity.

4.2.31 Optimal Bidding Strategy by GA with Retail and Interruptible Price

GA optimization is performed with interruptible prices ranging from [90,65,50] to [110,85,70]. The parameters used for GA are the same used before.

Table 4.59 Optimal Bidding Strategy by GA with Retail and Interruptible Price

α	0.96248
Retail price ($)	[178.88,153.89,135.24]
Interruptible price ($)	[84.347,75.056,56.611]
Bidding Price ($)	[100.23,94.056,89.025]
Quantity Cleared (MW)	30
Expected Profit ($)	2275.6
Standard deviation ($)	2407.5
Net profit ($)	2014.0

4.2.32 Comparison Analysis

Table 4.60 shows a comparison analysis of three scenarios discussed in tables 4.55, 4.57 and 4.59 the comparison done is shown in table 4.36. In Scenario1, the retail and interruptible prices are fixed to $[150, 100, 75] and $[110, 85, 70] respectively. The net profit using Monte-Carlo Simulation method was found to be $1285.2. In scenario2, the retail price was changed to $[179.93, 143.29, 139.91] by the optimization process where as the interruptible price was still fixed to $[110, 85, 70] and the net profit increased $ 2261.2. Finally, in scenario3 retail price and interruptible price were changed to $[178.88, 153.89, 135.24] and $[84.347, 75.056, 56.611] respectively by optimization process. The profit in scenario3 increased to 2014.0.

Table 4.60 Comparison Analysis

Factors	Scenario 1	Scenario 2	Scenario 3
Retail price ($)	[150,120,100]	[179.93,143.29,139.91]	[178.88,153.89,135.24]
Interruptible price ($)	[110,85,70]	[110,85,70]	[84.347,75.056,56.611]
α	0.99911	0.99321	0.96248
Quantity Cleared (MW)	30	30	30
Bidding price ($)	[118.8,97.286,88.411]	[109.85,97.142,88.841]	[100.23,94.056,89.025]
Expected profit ($)	1289.9	2312.6	2275.6
Standard deviation ($)	2452.2	2439.1	2407.5
Net profit ($)	1285.2	2261.2	2014.0

As the scenario3 involves high profit (less than scenario 2 with high risk) and low deviation with low risk value it should be preferred for optimal bidding strategy for single block bidding per unit time.

4.2.33 Comparison of TBB with and without Contract

Table 4.61 shows comparison of TBB with and without contract discussed in tables 4.53 and 4.60.

Table 4.61 Comparison of TBB with and without Contract

Factors	Scenario 1		Scenario 2		Scenario 3	
	TBB with Contract	**TBB without Contract**	**TBB with Contract**	**TBB without Contract**	**TBB with Contract**	**TBB without Contract**
a ($)	[150,120,100]	[150,100,75]	[179.93,143.29,139.91]	[177.07 153.37,132.31]	[178.88,153.89,135.24]	[178.04,158.14,133.79]
b ($)	[110,85,70]	[110,85,70]	[110,85,70]	[110,85,70]	[84.347,75.056,56.611]	[88.714,74.476,59.116]
α	0.99911	0.99539	0.99321	0.97178	0.96248	0.97481
Bidding price ($)	[118.8,97.286,88.411]	[117.53,95.249,88.879]	[109.85,97.142,88.841]	[109.84,94.991,88.041]	[100.23,94.056,89.025]	[117.7, 92.422,88.459]
$E(\pi)$ ($)	1289.9	747.05	2312.6	1700	2275.6	1827.9
$D(\pi)$ ($)	2452.2	2450.8	2439.1	2133.2	2407.5	2407.5
Net profit ($)	1285.2	724.87	2261.2	1504	2014.0	1662.8

It is observed from the table 4.61 that the profit obtained by LSE 3 at bus 27 while constructing optimal bidding strategy with contractual tools is more when compared to optimal bidding strategy without contracts. Hence LSEs at buses should undertake contracts in order to avoid price fluctuations at nodes and also to maximize their profit.

4.2.34 Comparison of TBB and SBB with One Contract

Table 4.62 shows the comparison between SBB and TBB per unit time involving bilateral contracts with one of available generators discussed in tables 4.43 and 4.60.

Table 4.62 Comparison of TBB and SBB with Contract

Factors	Scenario 1		Scenario 2		Scenario 3	
	TBB with Contract	**SBB with Contract**	**TBB with Contract**	**SBB with Contract**	**TBB with Contract**	**SBB with Contract**
a ($)	[150,120,100]	150	[179.93,143.29,139.91]	179.41	[178.88,153.89,135.24]	179.22
b ($)	[110,85,70]	110	[110,85,70]	110	[84.347,75.056,56.611]	93.989
α	0.99911	0.99171	0.99321	0.98735	0.96248	0.957
Bidding price ($)	[118.8,97.286,88.411]	98.746	[109.85,97.142,88.841]	87.263	[100.23,94.056,89.025]	87.76
$E(\pi)$ ($)	1289.9	2372.0	2312.6	3291.5	2275.6	3311.3
$D(\pi)$ ($)	2452.2	2026.7	2439.1	2235.9	2407.5	2407.5
Net profit ($)	1285.2	2284.0	2261.2	3132.0	2014.0	2789.2

The comparison shows that for single block bidding per unit time the profits turn out to be maximum in all the scenarios when compared to three block bidding per unit time. The reason for such difference is that in SBB the retail price at which LSE sells the electric power to the end customer is only one price e.g. $179.22 for scenario 3 for supplying 30 MW whereas for TBB it changes from block to block e.g. $[178.88,153.89,135.24] for supplying 30 MW in the order of 10MW for each block. The advantage of SBB optimal bidding strategy is that it can draw high profits but the disadvantage is that if the single price did not clear the market level then the LSE is out of business from the market and can clear the quantities only agreed on contracts. Thus it should pay the end customers the interruptible prices for the whole load as per agreement which is a loss. Whereas for TBB the profit might be less when compared to SBB but it has the advantage of clearing block quantities in the market according to its block bidding. It's on the LSE to select either of the strategies but before that it should ensure itself of the electricity market process and forecasted load. Researchers of electricity market adopt TBB or more than three block bidding per unit time to construct bidding strategies of market participants.

Bilateral Contracts with More than One Available Generators

When LSE at bus 27 undertakes bilateral trading of 26 MW with generator at bus 13 for $78 and a trade of 4 MW with generator at 23 for $82 then the optimal bidding strategy using SBB for LSE at 27 is shown in table 4.63. The settlement of contracts is shown in Appendix D. In scenario1, retail price and interruptible price are fixed to $[150,120,100] and $[110, 85, 70] respectively. The net profit in scenario 1 was found to be $1357.6. In scenario2, the optimal retail price was found to be $[179.93, 143.29, 139.91] and interruptible price is fixed to $[110, 85, 70] and net profit was found to be $ 2260. In scenario3, the optimal retail and interruptible prices were found to be $[178.88, 153.89, 135.24] and $ [84.347, 75.056, 56.611] with a net profit of $2172.9.

Table 4.63 Optimal bidding strategy using forward contracts with two generators

Factors	Scenario 1	Scenario 2	Scenario 3
Retail price ($)	[150,120,100]	[179.93,143.29,139.91]	[178.88,153.89,135.24]
Interruptible price ($)	[110,85,70]	[110,85,70]	[84.347,75.056,56.611]
α	0.99911	0.99321	0.96248
Expected profit ($)	1360	2291.3	2340.1
Standard deviation ($)	2452.2	2291.6	2340.4
Net profit ($)	1357.6	2260	2172.9

4.2.35 Comparison of TBB and SBB with More than One Contract

Table 4.64 shows the comparison of TBB and SBB with more than one contract from tables 4.63 and 4.55.

Table 4.64 Comparison of TBB and SBB with More than One Contract

Factors	Scenario 1		Scenario 2		Scenario 3	
	TBB with Contract	**SBB with Contract**	**TBB with Contract**	**SBB with Contract**	**TBB with Contract**	**SBB with Contract**
a ($)	[150,120,100]	150	[179.93,143.29,139.91]	179.41	[178.88,153.89,135.24]	179.22
b ($)	[110,85,70]	110	[110,85,70]	110	[84.347,75.056,56.611]	93.989
α	0.99911	0.99171	0.99321	0.98735	0.96248	0.957
$E(\pi)$ ($)	1360	2160.0	2291.3	3291.5	2340.1	3036.6
$D(\pi)$ ($)	2452.2	2160.3	2291.6	2090.5	2340.4	2070.2
Net profit ($)	1357.6	2124.2	2260	29654	2172.9	2775.5

The comparison shows that for single block bidding per unit time the profits turn out to be maximum in all the scenarios when compared to three block bidding per unit time. The reasons for such differences are same as mentioned in section 4.1.21. Out of all the comparisons made in Tables 4.44, 4.61, 4.63 and 4.64, the optimal bidding strategy constructed for LSE at bus 27 provides maximum profit when it undertakes bilateral trading with generators at bus 13 and at bus 23. The reason for this is that bilateral trading avoids the risk of price fluctuations that may occur due to transmission constraints in the network.

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 Conclusion

The thesis presents a literature review on electricity markets, electricity pricing rules and pricing settlements. Literature survey on demand side participation and its importance are documented. Different perspectives on accomplishment of DSP with respect to market participants were studied. The effects of transmission constraints on electricity market and the techniques used to manage transmission constraints are also documented. Finally, the various approaches of strategic bidding of market participants were discussed.

An optimal bidding strategy for LSEs is developed for a pool based double-sided auction electricity market covering two models. The first model neglects the effect of transmission constraints whereas the second model takes into account the impacts of transmission constraints on the profit of LSEs. In this market, sealed auction with pay-as-bid (PAB) settlement and step-wise bidding protocols are used. The bidding behaviors of rivals are represented as stochastic variables of normal probability distributions. The problem is then formulated as a multi-objective stochastic optimization model and solved by a Monte-Carlo Simulation and Genetic Algorithm (GA).

When there are no transmission constraints for a market model of 3 Gencos and 4 LSEs, the results obtained conclude that an LSE competing in double-sided electricity market should bid high and increase its retail price to the end customers in order to maximize its profit. Bidding high will reduce its profit but also reduces its risks of bidding-decision. Retail prices must not be increased so highly that customers may opt for other LSEs. LSE may also reduce its risk of bidding –decision by having higher proportion of important type of load customers. A comparative study is done to show the importance of TBB per unit time. It is shown that three block bidding (TBB) per unit time is more preferable than single block bidding (SBB) because TBB can clear the block quantities block wise with decreasing prices. Whereas, in SBB if market clearing price is greater than the single bid price then LSE will not clear any quantity from the market.

The techniques to manage transmission constraints are documented in the thesis. When the effects of transmission constraints are considered in the electricity model of IEEE-30 bus system, forward contracts are undertaken with generators at bus 13 and at bus 23 while building an optimal bidding strategy. At first, Optimal bidding strategy was constructed without forward contracts and then with forward contracts. The profit drawn from the bidding strategy constructed by considering contract between LSE at bus 27 and generators at bus 13, bus 23 was more profitable than bidding strategy without contracts. The reason for this increased profit was contract signed at low price increased the gap between retail price and a guarantee of clearing all MWs form contracted generators. A comparative study with TBB per unit time and SBB per unit time using forward contracts was done and the results shows that TBB per unit time bidding strategy is more effective than SBB per unit time.

5.2 Future Work

The further issues that can be addressed on building optimal bidding strategy are

- The effect of generator failure on the electricity market and on the profit of LSE can also be studied.
- Further study could include the impact of investing in generation and transmission by an LSE on strategic bidding.
- Management of ancillary services by an LSE in electricity markets can be studied.
- The bidding strategy can also be developed by using fuzzy theory and game theory approach and a comparative study can be done.
- Optimal bidding strategy can be developed for a micro-grid in the competitive electricity markets.

APPENDIX A

Bus data for IEEE-30 bus system

Bus No.	Type	Voltage		Load	
		Magnitude (pu)	Angle	P (MW)	Q (MVAR)
1	3	1	0	0	0
2	2	1	0	5.04	2.96
3	1	1	0	22.32	11.16
4	1	1	0	8.83	1.86
5	1	1	0	0	0
6	1	1	0	0	0
7	1	1	0	30	12
8	1	1	0	13.95	13.95
9	1	1	0	0	0
10	1	1	0	6.74	2.34
11	1	1	0	0	0
12	1	1	0	13.01	8.72
13	2	1	0	0	0
14	1	1	0	7.21	1.86
15	1	1	0	30	12
16	1	1	0	4.07	2.09
17	1	1	0	10.46	6.75
18	1	1	0	3.72	1.05
19	1	1	0	11.04	3.95
20	2	1	0	2.56	0.82
21	2	1	0	3.39	2.17
22	1	1	0	0	0
23	1	1	0	22.32	11.16
24	1	1	0	10.11	7.79
25	1	1	0	0	0
26	1	1	0	4.06	2.67
27	2	1	0	30	7.5
28	1	1	0	0	0
29	1	1	0	2.79	1.05
30	1	1	0	10.6	1.9

Line Data for IEEE-30 bus system

Line No.	From	To	R (p.u.)	X(p.u.)	B(p.u.)	Flow limit (MW)
1	1	2	0.02	0.06	0.03	130
2	1	3	0.05	0.19	0.02	130
3	2	4	0.06	0.17	0.02	65
4	3	4	0.01	0.04	0	130
5	2	5	0.05	0.2	0.02	130
6	2	6	0.06	0.18	0.02	65
7	4	6	0.01	0.04	0	90
8	5	7	0.05	0.12	0.01	70
9	6	7	0.03	0.08	0.01	130
10	6	8	0.01	0.04	0	32
11	6	9	0	0.21	0	65
12	6	10	0	0.56	0	32
13	9	11	0	0.21	0	65
14	9	10	0	0.11	0	65
15	4	12	0	0.26	0	65
16	12	13	0	0.14	0	65
17	12	14	0.12	0.26	0	32
18	12	15	0.07	0.13	0	32
19	12	16	0.09	0.2	0	32
20	14	15	0.22	0.2	0	16
21	16	17	0.08	0.19	0	16
22	15	18	0.11	0.22	0	16
23	18	19	0.06	0.13	0	16
24	19	20	0.03	0.07	0	32
25	10	20	0.09	0.21	0	32
26	10	17	0.03	0.08	0	32
27	10	21	0.03	0.07	0	32
28	10	22	0.07	0.15	0	32
29	21	22	0.01	0.02	0	32
30	15	23	0.1	0.2	0	16
31	22	24	0.12	0.18	0	16
32	23	24	0.13	0.27	0	16
33	24	25	0.19	0.33	0	16
34	25	26	0.25	0.38	0	16
35	25	27	0.11	0.21	0	16
36	28	27	0	0.4	0	65
37	27	29	0.22	0.42	0	16
38	27	30	0.32	0.6	0	16
39	29	30	0.24	0.45	0	16
40	8	28	0.06	0.2	0.02	32
41	6	28	0.02	0.06	0.013	32

Generation Data of IEEE-30 bus system

Gen No.	Bus No.	Pg(MW)	Qg(MVAR)	Qmax(MVAR)	Qmin(MVAR)	Pmax(MW)	Pmin (MW)
1	1	23.54	0	60	-15	60	0
2	2	60.97	0	60	-15	60	0
3	22	21.59	0	60	-15	60	0
4	27	26.91	0	60	-15	60	0
5	23	19.2	0	60	-15	60	0
6	13	37	0	60	-15	60	0

APPENDIX B

OPF Bus data without transmission constraints

Bus No.	Voltage		Generation		Load		Lambda ($/MVA-hr)	
	Mag (pu)	Angle	P (MW)	Q (MVAR)	P (MW)	Q (MVAR)	P	Q
1	1.060	0	60	-0.22	0	0	71.768	0.001
2	1.058	-0.911	60	24.50	5.04	2.96	72.435	0
3	1.031	-2.989	-	-	22.32	11.16	74.285	0.654
4	1.032	-3.211	-	-	8.83	1.86	74.490	0.615
5	1.037	-2.953	-	-	0	0	73.948	0.489
6	1.028	-3.838	-	-	0	0	75.114	0.637
7	1.019	-4.123	-	-	30	12	75.503	0.984
8	1.022	-4.185	-	-	13.95	13.95	75.465	0.781
9	1.035	-4.335	-	-	0	0	74.785	0.644
10	1.039	-4.592	-	-	6.74	2.34	74.614	0.650
11	1.035	-4.335	-	-	0	0	74.785	0.644
12	1.038	-2.990	-	-	13.01	8.72	74.318	0.599
13	1.060	1.389	60	19.03	0	0	73.272	0
14	1.023	-4.328	-	-	7.21	1.86	74.876	1.093
15	1.019	-4.736	-	-	30	12	75.716	1.169
16	1.030	-4.013	-	-	4.07	2.09	74.40	0.905
17	1.030	-4.664	-	-	10.46	6.75	74.893	0.927
18	1.011	-5.534	-	-	3.72	1.05	76.603	1.416
19	1.011	-5.774	-	-	11.04	3.95	76.734	1.451
20	1.017	-5.537	-	-	2.56	0.82	76.278	1.283
21	1.051	-4.467	-	-	3.39	2.17	74.022	0.184
22	1.056	-4.419	36	26.29	0	0	73.793	-0.001
23	1.051	-4.469	41.67	24.05	22.32	11.16	74.227	0.002
24	1.037	-5.949	-	-	10.11	7.79	75.758	0.764
25	1.033	-9.660	-	-	0	0	78.433	0.626
26	1.013	-10.140	-	-	4.06	2.67	80.028	1.694
27	1.044	-11.656	0	30.11	30	7.5	79.134	-0.001
28	1.024	-4.764	-	-	0	0	76.243	0.461
29	1.023	-12.898	-	-	2.79	1.05	81.303	0.616
30	1.013	-13.711	-	-	10.6	1.9	82.693	0.836
		Total:	**257.67**	**123.76**	**252.22**	**118.75**		

OPF Branch data without transmission constraints

Line No.	From	To	From Bus Injection P(MW)	Q(MVAr)	To Bus Injection P(MW)	Q(MVAr)	Loss (I^2 * Z) P(MW)	Q(MVAr)
1	1	2	27.82	-7.35	-27.68	4.42	0.143	0.43
2	1	3	32.18	7.13	-31.69	-7.45	0.491	1.87
3	2	4	28.19	5.71	-27.74	-6.61	0.451	1.28
4	3	4	9.37	-3.71	-9.36	3.75	0.010	0.04
5	2	5	21.10	5.08	-20.89	-6.41	0.216	0.86
6	2	6	33.34	6.34	-32.72	-6.64	0.626	1.88
7	4	6	29.86	3.35	-29.78	-3.01	0.085	0.34
8	5	7	20.89	6.41	-20.66	-6.93	0.225	0.54
9	6	7	9.38	7.13	-9.34	-8.07	0.042	0.11
10	6	8	18.58	10.74	-18.53	-10.56	0.044	0.17
11	6	9	4.39	-3.46	-4.39	3.52	0.000	0.06
12	6	10	2.51	-1.98	-2.51	2.03	0.000	0.05
13	9	11	0.00	-0.00	0.00	-0.00	-0.000	0.00
14	9	10	4.39	-3.52	-4.39	3.55	0.000	0.03
15	4	12	-1.59	-2.35	1.59	2.37	0.000	0.02
16	12	13	-60.00	-14.10	60.00	19.03	0.000	4.94
17	12	14	10.14	1.30	-10.02	-1.04	0.116	0.25
18	12	15	25.74	1.78	-25.31	-0.98	0.433	0.80
19	12	16	9.52	-0.06	-9.44	0.23	0.076	0.17
20	14	15	2.81	-0.82	-2.79	0.83	0.018	0.02
21	16	17	5.37	-2.32	-5.34	2.38	0.026	0.06
22	15	18	6.60	0.14	-6.55	-0.05	0.046	0.09
23	18	19	2.83	-1.00	-2.83	1.01	0.005	0.01
24	19	20	-8.21	-4.96	8.24	5.02	0.027	0.06
25	10	20	10.93	6.15	-10.80	-5.84	0.131	0.31
26	10	17	5.15	9.22	-5.12	-9.13	0.031	0.08
27	10	21	-9.60	-14.48	9.69	14.67	0.084	0.20
28	10	22	-6.32	-8.81	6.39	8.97	0.076	0.16
29	21	22	-13.08	-16.84	13.12	16.93	0.041	0.08
30	15	23	-8.49	-12.00	8.70	12.42	0.208	0.42
31	22	24	16.49	0.39	-16.20	0.05	0.293	0.44
32	23	24	10.65	0.48	-10.51	-0.20	0.134	0.28
33	24	25	16.60	-7.64	-16.01	8.66	0.590	1.03
34	25	26	4.12	2.76	-4.06	-2.67	0.058	0.09
35	25	27	11.89	-11.42	-11.61	11.96	0.280	0.54
36	28	27	32.06	-3.20	-32.06	7.17	0.000	3.96
37	27	29	6.45	1.78	-6.36	-1.61	0.090	0.17
38	27	30	7.22	1.70	-7.06	-1.40	0.162	0.30
39	29	30	3.57	0.56	-3.54	-0.50	0.030	0.06
40	8	28	4.58	-3.39	-4.57	1.35	0.015	0.05
41	6	28	27.64	-2.79	-27.49	1.86	0.145	0.44
						Total:	**5.449**	**22.69**

APPENDIX C

OPF Bus data with transmission constraints

Bus No.	Voltage		Generation		Load		Lambda ($/MVA-hr)	
	Mag (pu)	Angle	P (MW)	Q (MVAR)	P (MW)	Q (MVAR)	P	Q
1	1.060	0	60	-0.22	0	0	71.768	0.001
2	1.058	-0.911	60	24.50	5.04	2.96	72.435	0
3	1.031	-2.989	-	-	22.32	11.16	74.285	0.654
4	1.032	-3.211	-	-	8.83	1.86	74.490	0.615
5	1.037	-2.953	-	-	0	0	73.948	0.489
6	1.028	-3.838	-	-	0	0	75.114	0.637
7	1.019	-4.123	-	-	30	12	75.503	0.984
8	1.022	-4.185	-	-	13.95	13.95	75.465	0.781
9	1.035	-4.335	-	-	0	0	74.785	0.644
10	1.039	-4.592	-	-	6.74	2.34	74.614	0.650
11	1.035	-4.335	-	-	0	0	74.785	0.644
12	1.038	-2.990	-	-	13.01	8.72	74.318	0.599
13	1.060	1.389	60	19.03	0	0	73.272	0
14	1.023	-4.328	-	-	7.21	1.86	74.876	1.093
15	1.019	-4.736	-	-	30	12	75.716	1.169
16	1.030	-4.013	-	-	4.07	2.09	74.40	0.905
17	1.030	-4.664	-	-	10.46	6.75	74.893	0.927
18	1.011	-5.534	-	-	3.72	1.05	76.603	1.416
19	1.011	-5.774	-	-	11.04	3.95	76.734	1.451
20	1.017	-5.537	-	-	2.56	0.82	76.278	1.283
21	1.051	-4.467	-	-	3.39	2.17	74.022	0.184
22	1.056	-4.419	36	26.29	0	0	73.793	-0.001
23	1.051	-4.469	41.67	24.05	22.32	11.16	74.227	0.002
24	1.037	-5.949	-	-	10.11	7.79	75.758	0.764
25	1.033	-9.660	-	-	0	0	78.433	0.626
26	1.013	-10.140	-	-	4.06	2.67	80.028	1.694
27	1.044	-11.656	0	30.11	30	7.5	79.134	-0.001
28	1.024	-4.764	-	-	0	0	76.243	0.461
29	1.023	-12.898	-	-	2.79	1.05	81.303	0.616
30	1.013	-13.711	-	-	10.6	1.9	82.693	0.836
		Total:	**257.30**	**122.15**	**252.22**	**118.75**		

OPF Branch data with transmission constraints

Line No.	From	To	From Bus Injection P(MW)	Q(MVAr)	To Bus Injection P(MW)	Q(MVAr)	Loss (I^2 * Z) P(MW)	Q(MVAr)
1	1	2	28.30	-7.62	-28.15	4.70	0.149	0.45
2	1	3	31.70	7.24	-31.23	-7.61	0.478	1.82
3	2	4	27.42	6.01	-26.99	-6.97	0.430	1.22
4	3	4	8.91	-3.55	-8.90	3.59	0.009	0.03
5	2	5	20.60	5.25	-20.39	-6.62	0.208	0.83
6	2	6	32.23	6.74	-31.64	-7.15	0.590	1.77
7	4	6	28.12	3.90	-28.05	-3.60	0.076	0.30
8	5	7	20.39	6.62	-20.18	-7.15	0.217	0.52
9	6	7	9.87	6.92	-9.82	-7.85	0.043	0.12
10	6	8	17.94	10.70	-17.90	-10.54	0.041	0.17
11	6	9	4.32	-2.59	-4.32	2.64	0.000	0.05
12	6	10	2.47	-1.48	-2.47	1.52	0.000	0.04
13	9	11	0.00	-0.00	0.00	-0.00	-0.000	0.00
14	9	10	4.32	-2.64	-4.32	2.67	0.000	0.03
15	4	12	-1.07	-2.37	1.07	2.39	0.000	0.02
16	12	13	-60.00	-14.07	60.00	19.01	0.000	4.94
17	12	14	10.27	1.13	-10.15	-0.87	0.119	0.26
18	12	15	26.34	1.20	-25.89	-0.36	0.452	0.84
19	12	16	9.31	0.63	-9.24	-0.47	0.073	0.16
20	14	15	2.94	-0.99	-2.92	1.01	0.020	0.02
21	16	17	5.17	-1.62	-5.15	1.67	0.022	0.05
22	15	18	6.36	0.77	-6.32	-0.68	0.043	0.09
23	18	19	2.60	-0.37	-2.59	0.38	0.004	0.01
24	19	20	-8.45	-4.33	8.47	4.39	0.027	0.06
25	10	20	11.16	5.51	-11.03	-5.21	0.130	0.30
26	10	17	5.34	8.49	-5.31	-8.42	0.028	0.08
27	10	21	-9.95	-12.76	10.03	12.93	0.073	0.17
28	10	22	-6.51	-7.78	6.57	7.92	0.067	0.14
29	21	22	-13.42	-15.10	13.45	15.17	0.037	0.07
30	15	23	-7.55	-13.41	7.78	13.87	0.228	0.46
31	22	24	15.97	-0.92	-15.70	1.33	0.278	0.42
32	23	24	9.03	2.59	-8.92	-2.38	0.103	0.21
33	24	25	14.51	-6.75	-14.05	7.54	0.454	0.79
34	25	26	4.12	2.76	-4.06	-2.67	0.058	0.09
35	25	27	9.94	-10.29	-9.72	10.70	0.211	0.40
36	28	27	28.91	-3.16	-28.91	6.38	0.000	3.23
37	27	29	6.45	1.78	-6.36	-1.61	0.091	0.17
38	27	30	7.22	1.70	-7.06	-1.40	0.162	0.30
39	29	30	3.57	0.56	-3.54	-0.50	0.030	0.06
40	8	28	3.95	-3.41	-3.93	1.36	0.012	0.04
41	6	28	25.10	-2.81	-24.98	1.80	0.120	0.36
						Total:	**5.083**	**21.08**

Branch Flow Constraints

Line No.	From Bus	From MW End MW		Limit	To MW End MW		To Bus
31	22	17.598	16	16	15.75	-	24
33	24	17.453	16	16	15.95	-	25

APPENDIX D

SETTLEMENT OF CONTRACTS

Case2. When LSE at bus 27 undertake a contract with one of the available generators:

LSE at bus 27 pays $25 * 85.906 = \$2147.65$ to MO for extracting 25 MW at bus 27.

Generator at bus 13 receives $25 * 70.117 = \$1752.925$ from MO for injecting 25 MW at bus13.

LSE at bus 27 pays $25 * (78 - 70.117) = \$197.075$ to Generator at bus 13 to settle the contract for difference.

LSE at bus 27 collects $25 * (85.906 - 70.117) = \$394.725$ from MO for the FTRs it owns between bus 13 and bus 27.

Thus, LSE at bus 27 pays $\$1950$ for 25 MW which is equivalent to a price of $78\ \$/\mathrm{MWh}$

Case3. When LSE at bus 27 undertake contracts with more than one available generator:

1. Between LSE at bus 27 and generator at bus 13

LSE at bus 27 pays $26 * 85.906 = \$2233.556$ to MO for extracting 26 MW at bus 27.

Generator at bus 13 receives $26 * 70.117 = \$1823.042$ from MO for injecting 26 MW at bus13.

LSE at bus 27 pays $26 * (78 - 70.117) = \$204.958$ to Generator at bus 13 to settle the contract for difference.

LSE at bus 27 collects $26 * (85.906 - 70.117) = \$410.514$ from MO for the FTRs it owns between bus 13 and bus 27.

Thus, LSE at bus 27 pays $\$2028$ for 26 MW which is equivalent to a price of $78\ \$/\mathrm{MWh}$.

2. Between LSE at bus 27 and generator at bus 23

LSE at bus 27 pays $4 * 85.906 = \$343.624$ to MO for extracting 4 MW at bus 27.

Generator at bus 13 receives $4 * 74.126 = \$296.504$ from MO for injecting 4 MW at bus13.

LSE at bus 27 pays $4 * (82 - 74.126) = \$31.496$ to Generator at bus 13 to settle the contract for difference.

LSE at bus 27 collects $4 * (85.906 - 74.126) = \$47.12$ from MO for the FTRs it owns between bus 13 and bus 27.

Thus, LSE at bus 27 pays $\$328$ for 4 MW which is equivalent to a price of $82\ \$/\mathrm{MWh}$

NOMENCLATURE

Abbreviation	Full form
Genco	Generation Company
LSE	Load Serving Entity
ISO	Independent System Operator
MO	Market Operator
MCP	Market Clearing Price
PAB	Pay-As-Bid
SBB	Single Bidding Block
TBB	Three Bidding Block
GA	Genetic Algorithm
DSP	Demand Side Participation
LAO	Last Accepted Offer
FRO	First Rejected Offer
LAB	Last Accepted Bid
FRB	First Rejected Bid
OPF	Optimal Power Flow
LMP	Locational Marginal Price
ZMCP	Zonal Market Clearing Price
NP	Nodal Price
FTRs	Financial Transmission Rights
FGRs	Flow Gate Rights

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