OPTIMAL PARTICIPATION OF POWER GENERATING COMPANIES IN A DEREGULATED ELECTRICITY MARKET

A Thesis Submitted to the College of

Graduate and Postdoctoral Studies

In Partial Fulfillment of the Requirements

For the Degree of Master of Science

In the Department of Electrical and Computer Engineering

University of Saskatchewan

Saskatoon

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ABSTRACT

The function of an electric utility is to make stable electric power available to consumers in an efficient manner. This would include power generation, transmission, distribution and retail sales. Since the early nineties however, many utilities have had to change from the vertically integrated structure to a deregulated system where the services were unbundled due to a rapid demand growth and need for better economic benefits. With the unbundling of services came competition which pushed innovation and led to the improvement of efficiency.

In a deregulated power system, power generators submit offers to sell energy and operating reserve in the electricity market. The market can be described more as oligopolistic with a System Operator in-charge of the power grid, matching the offers to supply with the bid in demands to determine the market clearing price for each interval. This price is what is paid to all generators. Energy is sold in the day-ahead market where offers are submitted hours prior to when it is needed. The spot energy market caters to unforeseen rise in load demand and thus commands a higher price for electrical energy than the day-ahead market. A generating company can improve its profit by using an appropriate bidding strategy. This improvement is affected by the nature of bids from competitors and uncertainty in demand. In a sealed bid auction, bids are submitted simultaneously within a timeframe and are confidential, thus a generator has no information on rivals' bids. There have been studies on methods used by generators to build optimal offers considering competition. However, many of these studies base estimations of rivals' behaviour on analysis with sufficient bidding history data from the market. Historical data on bidding behaviour may not be readily available in practical systems. The work reported in this thesis explores ways a generator can make security-constrained offers in different markets considering incomplete market information. It also incorporates possible uncertainty in load forecasts.

The research methodology used in this thesis is based on forecasting and optimization. Forecasts of market clearing price for each market interval are calculated and used in the objective function of profit maximization to get maximum benefit at the interval. Making these forecasts includes competition into the bid process. Results show that with information on historical data available, a generator can make adequate short-term analysis on market behaviour and thus optimize its benefits for the period. This thesis provides new insights into power generators’ approach in making optimal bids to maximize market benefits.

ACKNOWLEDGEMENTS

I wish to express my sincere gratitude and appreciation to my supervisor, Dr. Nurul A. Chowdhury, for giving me the opportunity to work with him. His patience, guidance, and support helped immensely in carrying out the research work and preparing this thesis. I'd also like to thank my other graduate studies professors; Dr. Rajesh Karki, Dr. Ramakrishna Gokaraju, and Dr. Sherif O. Faried, for their contributions to my pursuit of this degree, giving me a better understanding of power systems operation. I appreciate my colleagues in the power systems research group for the discussions and encouragement.

To my parents, Dr. and Mrs. E. O Oriola, and my brothers (Vincent and Victor), you let me spread my wings and push when I think I can go no further. Thank you for always believing in me, your unwavering support, and encouragement to be the best version of myself. 'The small girl with big dreams' appreciates all the sacrifices. To Ifeyomi, a million and many more thanks to my awesome friend and confidant, the best is yet to come.

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LIST OF ABBREVIATIONS

AESO	Alberta Electric System Operator
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
CAISO	California Independent System Operator
COPT	Capacity Outage Probability Table
DAM	Day-ahead Market
DISCOs	Distribution Companies
DP	Dynamic Programming
DSHW	Double Seasonal Holt-Winters
FERC	Federal Energy Regulatory Commission
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GENCOs	Generation Companies
GSSO	Golden Section Search Optimization
IESO	Independent Electricity System Operator (Ontario)
IPPs	Independent Power Producers
ISO	Independent System Operator
LDC	Local Distribution Company
LFU	Load Forecast Uncertainty
LMP	Locational Marginal Price
MA	Moving Average
MCP	Market Clearing Price
NUGs	Non-Utility Generators
NYISO	New York Independent System Operator
RESCOs	Retail Energy Services Companies
SFE	Supply Function Equilibrium
SM	Spot Market
SR	Spinning Reserve
TRANSCOs	Transmission Companies

CHAPTER 1

INTRODUCTION

1.1 Electric Power System

An electric power system is a complex network of generating stations, transmission lines and distribution stations that supply electrical energy to consumers. Traditionally, the task of electricity production, transmission and supply to consumers is handled and managed by an electric utility. An electric utility in the traditional regulated electric power industry is a vertically integrated monopoly as it is responsible for all activities related to electricity supply.

Electric power can be generated utilizing different techniques. A thermal generating station uses heat energy to produce electric power. Examples of thermal power plants are coal-fired units, nuclear units and gas turbines. Hydropower stations generate electric power with energy from water at high pressure. Other renewable sources of generation are solar, wind, biofuels and geothermal. Hydroelectricity is still the most popular form of renewable power supply, although there are ongoing studies on ways to largely improve electricity production from wind and solar.

Moving electric power from points of generation to where it is distributed to different customers is done with transmission lines. The transmission network of a region consists of several interconnected electric power lines that may consist of underground cables and overhead lines. Electric power is moved under high voltage through these lines to distribution substations.

At the distribution substation, the voltage is stepped down before sending power to the bulk customers. Power is moved through the distribution system to consumers at different service levels. Distribution lines can either be overhead; with utility poles, or underground.

1.2 Deregulation in Electric Power Industry

Before the nineties, electric power industries across the world were in most part regulated entities. Due to huge capital investment necessary to build and operate, a regulated environment created by governments made risk management possible [1][2]. Monopolies were set up to insure local utilities against unfavorable competition [2]. Regulated utilities made a steady growth of the electric power industry possible. To effectively manage operations, a regulated utility was under obligation to provide services at the least cost to all customers within its region [1]. The traditional electric utility was responsible for power generation, transmission, distribution, metering, billing, maintenance and repair, and all other activities related to electricity supply and use in its jurisdiction. However, with growth in technology and demand for electricity, came a need for innovation. Deregulation brought about competition which pushed innovation to improve quality and lower electricity price.

Deregulation can broadly be defined as removal or reduction of government's influence in an industry. In recent times, the need for this in the electric power industry became an important issue in many regions mainly due to a large increase in power demand and inefficient electricity pricing system. In a deregulated environment, the three major components (power generation, transmission, and distribution) of the electric power industry are unbundled. The main aim of deregulation in the electric power industry is to encourage competition among power producers and among retailers [1]. To ascertain fair competition, an open access transmission and distribution system is practiced. An open access system gives equal rights to generators or retailers to use the power grid for energy delivery to any location within the system. Coordinating the whole process brought the need for an Independent System Operator (ISO); an organization whose function is to manage the operations of the power grid in a region. The functions of a typical ISO will be further discussed in the next Chapter. The entities in a restructured power industry can be categorized into market operator and market participants [3]. The market operator is the ISO and generally, market participants are generation companies (GENCOs), transmission companies (TRANSCOs), distribution companies (DISCOs), retail energy services companies (RESCOs), and customers. In some regions, the local distribution companies are also the retail service providers.

As previously stated, with the operation of a competitive generation market, GENCOs own and/or operates facilities to produce bulk electric power and makes offers to sell the power in the electricity market. GENCOs have the option to sell their electric power under bilateral contracts and can participate in energy market auctions arranged by an ISO. They can sell power at whatever location and price with their revenue coming only from the sale of power produced.

GENCOs can participate in the market for ancillary services by providing operating reserves, frequency and voltage regulation, they can also make capacity offers in the capacity market. Examples of GENCOs are independent power producers (IPPs) or non-utility generators (NUGs). GENCOs inform the ISO of an impending scheduled maintenance outage and ISO gives approval based on system reliability constraints [3]. Sale of electric power is an 'on-site' transaction, transmission lines are required to move power to consumers. TRANSCOs own and maintain facilities for moving bulk power from point of production to DISCOs for distribution to customers. Transmission lines efficiently move large amount of power over long distances to distribution stations. In many regions where a deregulated environment is practiced, a TRANSCO may still operate as a regulated monopoly with unbiased connections for transport of power. This is maintained to remove complexities that may arise with the use of transmission lines and the method has been found to be beneficial to the public [1]. A regional operator (ISO) is responsible for the operation of the transmission system. However, TRANSCOs are paid for the use of their facilities through access charges, transmission usage charges and congestion revenues [3]. There can be more than one TRANSCO within a regional grid, but each would have its own jurisdiction or coverage area. The transmission sector is devoid of competition. DISCOs own and operate facilities for the distribution of power to consumers. A DISCO is a regulated company that obtains its revenue from the use of its distribution lines for delivery of electric power. In regions where DISCOs are also in charge of retail services, they buy electricity from the wholesale market or enter into bilateral contracts with GENCOs for the purchase of electric power and sell to customers through the distribution system (an illustration of this is the local distribution company). DISCOs are responsible for maintenance and availability of the distribution system as well as responding to outages and power quality issues in the system [3]. The RESCOs are responsible for retail sale of electric power and other energy-related services to consumers. They operate in a competitive environment, buying bulk electric power from GENCOs to sell to end-users through the distribution system. A RESCO can offer demand-side management services to customers, designing efficient ways to use energy. Customers are home-owners, small businesses (interacting with RESCOs) or large factories and industries (connected to the transmission system) who are end-users of electric power. In a deregulated environment, a customer has the choice of buying power from different RESCOs and can also buy directly from a GENCO.

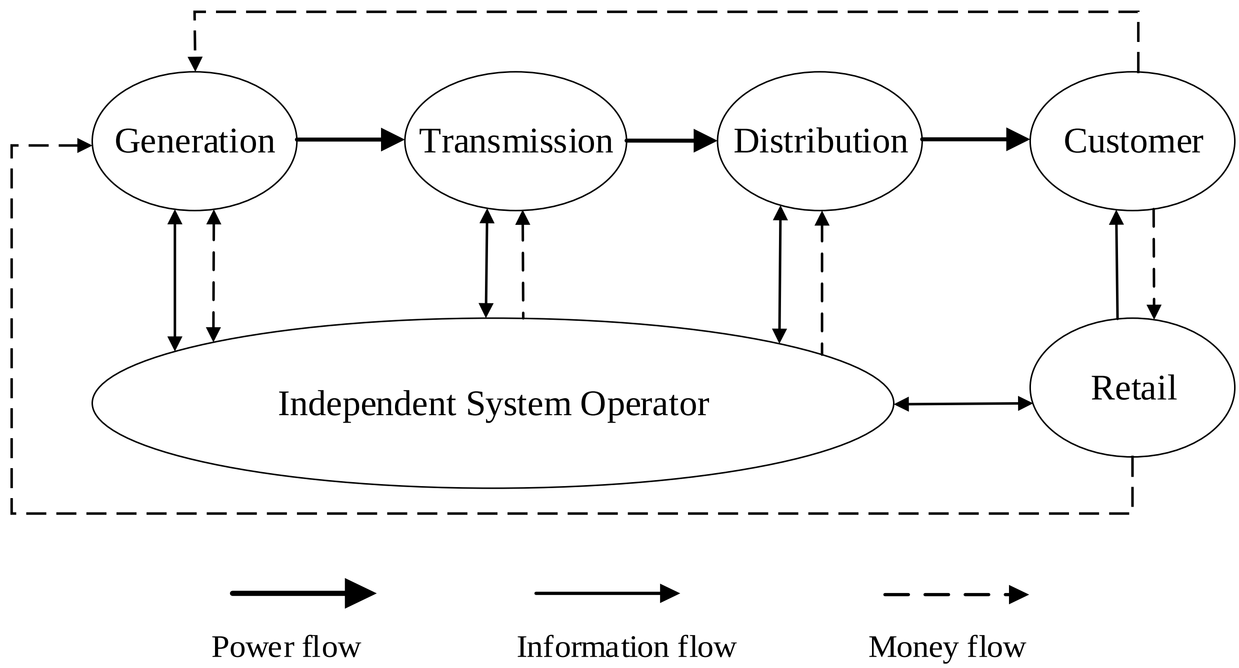

Fig. 1.1 Structure of a deregulated electric power industry

Deregulation encourages new measures for investment in the power industry. Cleaner and more productive methods for power generation are on-going in many regions. Market participants find ways of improving their services despite competition, saving cost and maximizing profit. Competition also brings efficiency, lowering electricity price. Customer experience/service improves as customers have options for retail energy providers. An optimal operation of the power system is achieved through deregulation.

1.3 Power System Reliability

The term 'Reliability' in engineering is generally understood to mean the probability that a component or system will perform its prescribed function without failure within a given time period when operated correctly in a stipulated environment. Improved reliability became a necessity due to the need for more complex functions to be performed by a single system, systems being used in increasingly hostile environments, pressure from the public on product performance and failure rate, competition among manufacturers, and many other factors. Critical systems and networks such as the electric power system require a high reliability over a long period. Maintaining reliability in electric power system requires evaluation of the system for adequacy and security [4]. Adequacy relates to having enough capacity or facilities to meet the demand for electricity at every point while security refers to the ability of the system to react to contingencies or disruptions [3][5]. Unstable conditions arising in the system can be due to weather, loss of generation, or equipment failure. In general, a reliable power system should have sufficient generation and transmission facilities to meet demand, be able to accommodate uncertainty in demand and loss of generation and maintain steady frequency and voltage at an acceptable level. In a bid to ensure resource adequacy and system security, one of the tools used in power system planning and operation is Load Forecasting.

1.3.1 Load Forecasting

Load forecasting is a form of prediction of consumers' electricity demand over a period to make adequate commitments for supply. This is an important part of planning and operation in a power system. To make a good forecast, analysis is done on data considering factors such as temperature, wind chill, historical data on demand and price, climate change and day of the week. Forecasts can be short-term (hours to a few days ahead), medium-term (few weeks to months ahead) or long-term (years ahead). Short-term forecasts are applied in scheduling daily generation and supply of electricity, maintaining system stability. Medium-term forecasts are used in outage and maintenance planning, scheduling fuel purchases and generation optimization. Long-term forecasts are employed for investment planning purposes such as capacity expansion. Some techniques used in electricity load forecasting are discussed in [6]. While the use of good forecasting models would give highly accurate results, and thus higher operating reliability of the power system, it is nonviable to expect an exact demand for electricity in real-time. This inexactness is due to complexities with electricity demand as there are many uncontrollable factors that determine its quantity.

1.3.1.1 Load Forecast Uncertainty

Load forecast uncertainty (LFU) is the variability associated with the prediction of load demand. LFU is an essential part of electric power system operation. The system's operating cost increases with spare generation capacity kept to accommodate contingencies like sudden increase in demand, an accurate load forecast usually minimizes this since quantity on reserve would be minimal. However, irrespective of how meticulously forecasts are made, it is unlikely that real-time demand would be exact since forecasts are mainly based on experience. LFU affects the quantity of resources to be committed to have adequate capacity in the system. It is an important factor to be considered in units scheduling and dispatch as it affects the reliability of the system. Uncertainty in load can be described by a normal distribution as proposed by many authors [4][6][8][9], with the distribution mean, μ, as the forecast peak load and standard deviation, σ, as level of uncertainty. A normal distribution can be divided into discrete number of class intervals. The designated probability of an interval relates to the probability of the load within that interval [4]. A distribution with five class intervals (5-step) is shown in Fig. 1.2, which is adequate for LFU representation in the research work done. Dividing the distribution into seven class intervals is also a popular approach by researchers to model LFU.

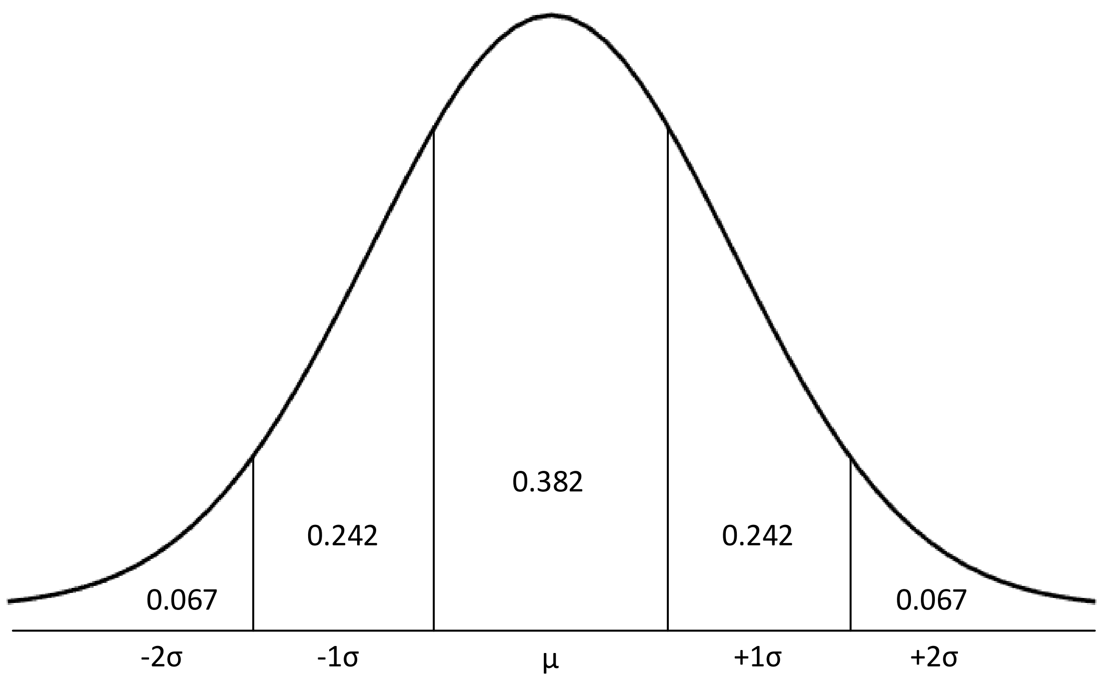

Fig. 1.2 5-step approximation of the normal distribution for load forecast uncertainty

1.4 Objectives and Thesis Outline

This thesis examines ways power producers can maximize their daily benefits by making optimal offers to supply electricity to the market while maintaining their system security. The objectives of this research are:

1. To determine the hourly price/quantity offers to submit in the day-ahead market bid process for maximum benefit.
2. To determine the quantity of spinning reserve needed to be maintained with each offer to ensure the generator's system security in the event of an emergency.
3. To determine the price/quantity offers that can be submitted in the spot market.
4. To study the effects of LFU on hourly price/quantity offers made in the day-ahead and spot markets.

The overall structure of this thesis takes the form of five chapters, including the current chapter. Chapter 2 begins by describing functions of an Independent System Operator. This Chapter defines what a market clearing price is and provides examples of electricity market. Review of literature on market modelling and optimal bidding by power producers in the day-ahead electricity market is also discussed.

Chapter 3 discusses the methodology used for this research work. Electricity price forecasting with the double seasonal Holt-Winters model is described. Price forecasting is a reliable way of determining optimal prices for offers made in the bid process. The golden section search method as an optimization algorithm for calculating optimal quantity to be offered is discussed. Dynamic programming for economic dispatch after deciding on hourly price/quantity pairs is also included in this Chapter.

Chapter 4 presents the results. A sample test system and load model are used to demonstrate the methodology stated in the previous Chapter. Results are discussed based on different scenarios with the effect of LFU on the strategy employed.

Conclusions derived from the work and suggestions for future work are outlined in Chapter 5.

CHAPTER 2

ELECTRICITY MARKETS IN DEREGULATED POWER SYSTEM

2.1 Introduction

With the advent of deregulation in the electric power industry, the number of participants who provide different services related to the production, transmission and distribution of electricity increased. It became necessary to have an independent system operator (ISO) to monitor that the bulk customers receive stable, reliable and secure delivery of electric power. An ISO is also responsible for a safe operation of the power system. To achieve an efficient operation, several market processes are implemented with different timelines. Generators and retailers take part in these markets and offer other services to help maintain system reliability. This Chapter explains the responsibilities of the ISO. It describes wholesale energy markets and services for secure system operation. Relevant literature on the structure and modelling of a wholesale electricity market and strategic participation of power producers in day-ahead auction process are also presented in this Chapter.

2.2 Independent System Operator

In a deregulated power system, an ISO is an entity that manages operation to provide all market participants open-access to wholesale and retail markets [3]. It is independent of other market participants such as the consumers, generating companies, distribution companies and transmission owners. It ensures an economic operation by balancing the energy market every hour of the day for customers to receive supply when needed at the lowest possible price. An ISO determines the price commonly known as market clearing price that the suppliers will receive. Unit commitment and economic dispatch of resources are done to ensure system security by frequency regulation, voltage control, load following and managing congestion in transmission lines. Market forecasting, load and price forecasting, are also done by an ISO [3]. An ISO takes proper steps to maintain the safety and reliability of the system. Some ISOs operating in North America are Ontario’s Independent Electricity System Operator (IESO), Alberta Electric System

Operator (AESO), California Independent System Operator (CAISO) and New York Independent System Operator (NYISO).

2.2.1 Electricity Market Clearing Price

The ISO makes hourly forecast of expected demand for trade day weeks ahead, making necessary adjustments as the day approaches. Based on these forecasts, power producers or generators submit offers to supply in price/quantity pairs while consumers also submit bids in same manner in the electricity market. The price/quantity pair states the quantity a producer can supply and the minimum price acceptable or the quantity a consumer is willing to buy and the maximum price that can be paid [10]. Bids or offers can be submitted for any or all hours of the trade day. An ISO arranges offers from the cheapest to the most expensive against demand. Market supply curve, showing offer price as a function of cumulative offer quantity, is built from this ranking. Similarly, the market demand curve is built from ranking consumers' bids in a decreasing order of price. Price at the point of equilibrium where there is a balance between supply and demand for energy is the market clearing price (MCP).

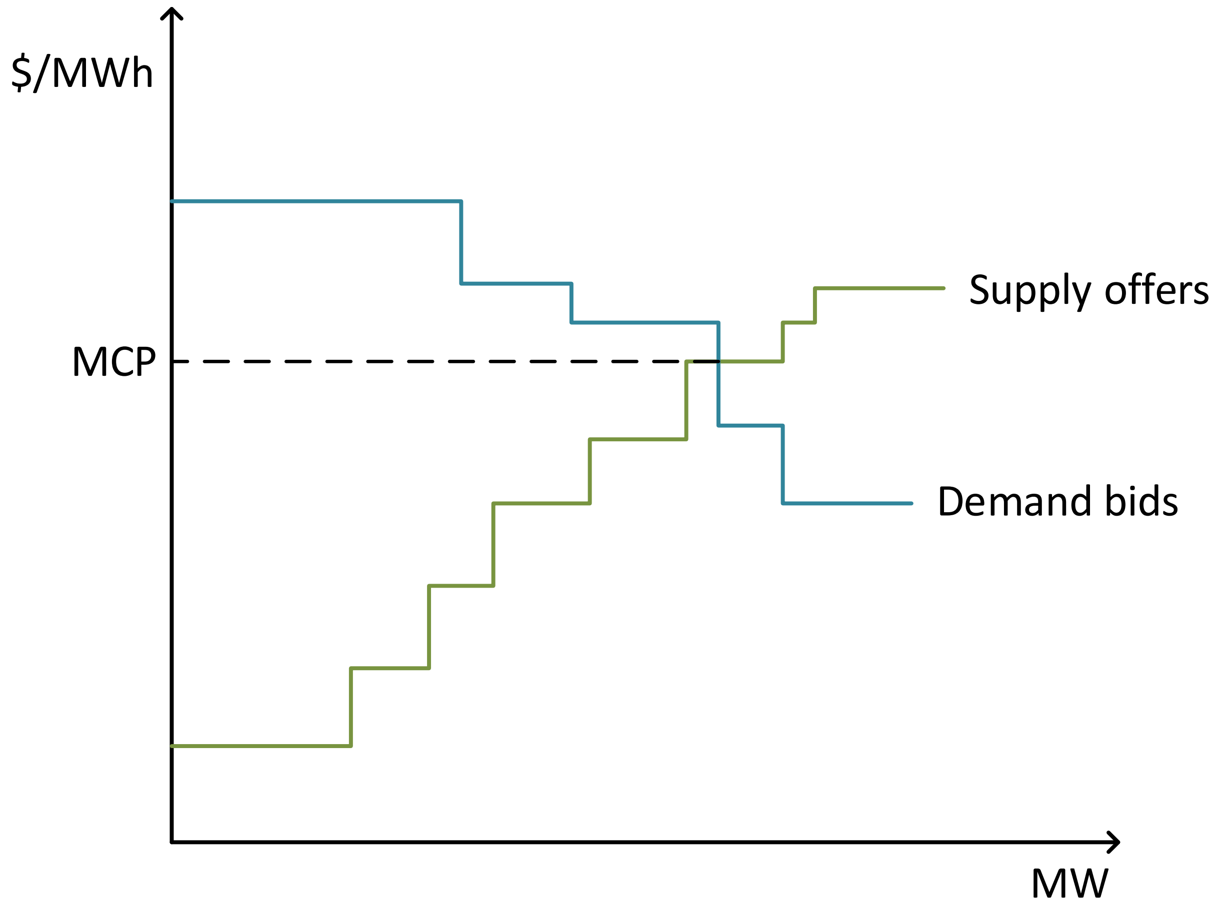

Fig. 2.1 Electricity market clearing price

All generators with prices below or equal to the MCP would be scheduled to supply for that auction interval. The MCP is paid to these generators irrespective of what their offer price was. This single price method improves efficiency in the power grid as electricity is being supplied at the least possible cost, encourages investment in generation and limits market manipulation.

As explained in [10], there are dispatchable and non-dispatchable generators and loads or consumers. A dispatchable generator would submit offers in the wholesale electricity market, taking active part in the auction process, and respond to dispatch instructions when scheduled to supply. These generators must be able to adjust their amount of generation in response to ISO's dispatch instructions. Examples are: coal-fired, nuclear and hydro-electric power generating facilities. Dispatchable loads also submit bids to buy energy and respond to instructions on how to manage their consumption. These dispatchable loads can provide operating reserve to handle contingencies in the system [11]. Dispatchable facilities help maintain reliability and efficient operation of a power grid by responding to instructions to manage congestion, providing operating reserves for frequency regulation and continuous balance of energy supply and demand [10]. Dispatch instructions consider participant's ability to adjust its generation or consumption levels. Non-dispatchable generators submits estimates of energy production instead of price/quantity offers while non-dispatchable loads draw electricity from the power grid as needed. These generators and loads are price-takers, meaning they accept the MCP for their supply or consumption. This makes non-dispatchable generators the least expensive and thus, considered first in the process of determining MCP. Wind, solar photo-voltaic and run-of-the-river hydro generating facilities are examples of non-dispatchable generators. A good example of non-dispatchable load is the local distribution company (LDC). The LDC takes electricity from the grid and distributes to retail consumers at a lower voltage. Most of the energy consumed in ISO-controlled grids of many regions are non-dispatchable loads.

2.3 Unit Commitment

Unit commitment is a decision process to determine the starting, stopping and generation output schedule of generating units to satisfy varying demand over a period of time. This process finds the optimal schedule for units present in a power grid to supply power such that the total operating cost for the period becomes minimum [12]. Schedules generated from unit commitment depend on demand and reserve requirement, amongst other constraints. In a regulated environment, since all generation is from same entity, reserve requirement is integrated directly into the unit commitment process, hence system adequacy is easily covered. This would still apply to GENCOs in a deregulated environment in estimating optimal offer schedules and minimizing cost. When an ISO publishes accepted offers from the market process, winning GENCOs are under contract to supply as scheduled. A GENCO would incorporate provision for unforeseen events such as sudden loss of generation in its unit commitment and operating schedule process to ensure there's adequate capacity to supply as stated in its offer. This can be termed spinning reserve requirement on generating side for GENCO's system security. Quantity on reserve and reserve allocation are determined by each GENCO. The ISO is however responsible for overall unit commitment on the power grid. From the unconstrained optimization run to calculate MCP, the ISO determines units to be committed to economically satisfy demand. For electric power system reliability in a restructured environment, spinning reserve is not embedded in the unit commitment process. Reserve requirements are procured in a separate market from that for bulk energy.

Minimizing fuel cost of different power plants while maintaining sufficient supply to meet demand is an important part of power system operation. The minimization problem would consider demand, reserve requirements and generating units constraints [13]. Power systems or reliability councils may set different rules on committing units depending on demand curve characteristics, generation side structure, and other related factors [14]. Generating units constraints as described in [14] include minimum up time and minimum down time, for thermal generating units. Minimum up time is the least period a unit committed and running should be left operating before turning off while minimum down time is the least period a unit decommitted should be left off before being recommitted. Also, since temperature and pressure changes in thermal units is a gradual process, taking some hours and energy to bring units on-line, there is an associated start-up cost. The start-up cost varies from cold-start (if the unit has been off for a while) to a value for when unit is off, but temperature is still close to operating temperature. The latter usually referred to as 'banking' requires just enough energy in the boiler to maintain operating temperature. Effect of maintenance and unplanned outages as they affect capacity limits of thermal units and units that have the 'must-run' status should also be considered in unit commitment [14]. Other unit operating constraints are the minimum and maximum operating limits which defines the generation output range. There is also the unit response rate limitation. The unit response rate or ramp rate is the rate of change in a unit's instantaneous output, usually measured in minutes. For system reliability and economic operation, ramp rate limits is an important consideration as it would ensure there is adequate committed capacity to accommodate changes in generation [15][16]. Common techniques in solving the unit commitment problem such as the priority-list method, Lagrange relaxation, dynamic programming, simulated annealing, evolutionary and swarm algorithms are described in [13][14]. Solution to unit commitment would have generation schedules, reserve and regulation market schedules as outputs, for every period committed units should be able to generate enough power to satisfy peak demand.

2.4 Energy Markets

Electricity markets operate on basic principle of demand and supply. MCP is the price at equilibrium point of supply and demand. Energy market is where the competition for buying and selling of electricity happens. The day-ahead and spot markets are types of energy market for wholesale trade of electricity. Respective ISOs in most jurisdictions operate the energy market.

2.4.1 Day-ahead Market

A day-ahead market (DAM) is a forward market for energy needed at each hour of the following day. It opens days prior to the trade day (7 days in CAISO) and closes a day before the trade day. It operates on a single schedule market design, with timeline before real-time energy market and use. An ISO determines the least expensive means of satisfying demand and then procures ancillary services. Ancillary services are procured through bid submissions and can be through a systemwide auction or on zonal basis [3]. DAM encourages transparency in electricity pricing and reduces price uncertainty, limits unfavourable strategic gaming by power producers and enables consumer participation in the trade of electricity [17]. It improves production certainty for dispatchable generators and reduces operational uncertainty between day-ahead schedules and real-time demand [18].

In a day ahead scheduling process, an ISO accepts submissions of supply offers, import offers, demand bids, export bids, and estimated output and consumption level of self-scheduling generators and loads, to optimize energy and operating reserve while considering system's reliability requirements for the trade day. Importers are those market participants who make offers (in a similar manner to dispatchable generators) to sell energy not generated originally in the ISO's jurisdiction but in neighbouring areas with which the ISO's power grid has interconnection. Exporters are market participants who submit bids (like large consumers/dispatchable loads) advising quantity of energy to consume and price. Since power import and export is done through the transmission lines and systems controlled by an ISO, they are factored into the market process to maintain system reliability. An ISO ensures availability of adequate resources to meet the next day's demand and balances generation and demand at every hour or interval, at minimum production cost. MCP is determined at the balance point between supply and demand at that interval. This MCP is set ignoring transmission constraints or congestion. After determining the MCP and energy schedule, an ISO runs a security constrained load dispatch. This would consider limitations such as losses, congestion and transmission constraints. The security constrained scheduling process notes the physical characteristics of the grid [10], dispatch schedule for the interval is an output of this process. This way, reliability is maintained in a grid.

A security constrained scheduling process is what produces the locational marginal price (LMP) which is zonal energy price. Since degree of constraints on the delivery of energy at zones or locations controlled by an ISO may vary, energy price at zones differs. The LMP is energy price at a specific location. Depending on the region, rules on market timelines may differ. However, continuous balance between energy supply and demand must be maintained within a close margin.

2.4.2 Spot Market

A spot market (SM) also known as real-time market is a market to maintain continuous balance of supply and demand for energy on the trade day. A DAM is operated with load forecasts, however, regardless of how ISOs and the market participants carefully make these forecasts, there are usually slight variations between forecasts and real-time demand. A SM is an avenue for utilities to procure additional energy needed to meet demand when real-time demand is more than forecast made [19]. Deviations from the day-ahead schedules which can't be covered by operating reserve are settled at the SM. Since delivery time for energy procured in this market is very short, price is usually very high. Bids and offers are submitted in a SM in a similar process as in a DAM but within a shorter timeline, dispatch and delivery is done in minutes. An ISO monitors and operates a SM, serving demand in the least expensive way. Balancing of energy in real-time is done within 15 to 5 minutes interval. This makes a SM operation a continuous process.

2.5 Capacity Market

A capacity market is a kind of 'future' market to ensure there would be enough resources in the grid to constantly meet demand. This translates to having the resources to meet the projected peak demand within a timeframe. Power producers make offers to supply capacity in a capacity auction. These auctions take place years before their operating period, the market is settled with capacity payments [20]. The single pricing system of paying all 'winning' generators the MCP is also adopted in this market.

A capacity market reduces the probability of having spikes in the wholesale price of electricity due to insufficient supply [21]. It helps with real-time electricity price volatility. The market encourages investment in power generation, maintaining the current resources, and pushes innovations for more sustainable and cleaner ways of generating power [20][21]. A capacity market would reduce the likelihood of a blackout.

2.6 Ancillary Services

Ancillary services are essential for the safe, secure and reliable operation of a power system. Federal Energy Regulatory Commission (FERC) defined ancillary services as 'those services necessary to support the transmission of electric power from seller to purchaser, given the obligations of control areas and transmitting utilities within those control areas, to maintain reliable operations of the interconnected transmission system' [22]. ISOs have differing lists of these services. They can however be grouped based on operation as frequency control/regulation, voltage control, and black start facilities for system restart. An ISO maintains a reliable grid by ensuring continuous supply of power under stable voltage and frequency.

a. Voltage Control: there are two products from power generation; real power and reactive power. Real power is what is supplied as electricity. Voltage in the system must be maintained within a close margin to the required level (between 95% and 105% of the nominal). Reactive power supports voltage stability. High level of reactive power raises voltage in the grid while voltage drops when reactive power is low. Synchronous generating units can be used to manage voltage by making changes in their operating conditions to either supply or absorb reactive power [23].
b. Frequency Control/Regulation: maintaining the system frequency at operating level (60Hz in North America) is important for reliability and stability. An imbalance between energy supply and demand causes the system frequency to change. When supply is higher than demand, there is a surplus, frequency goes up and this can lead to damage of plugged electrical devices by consumers. A 'regulation down' is required to correct this. If demand is higher than supply, there is a deficit in the system, frequency drops which leads to blackouts or brownouts. 'Regulation up' is required to correct this. Generating units

ramping up or down, units' inertia, demand response and more recently energy storage, are means of regulating frequency in an electric power system [24].

- Operating Reserve: this is used to offset imbalance between energy supply and demand to maintain reliability in the presence of an unexpected event. The unexpected incident can be sudden loss of generation, loss of transmission lines or sudden increase in demand. The Ontario IESO describes operating reserve as 'stand-by power or demand reduction that can be called on with short notice to deal with an unexpected mismatch between generation and load' [25]. Operating reserve can be divided into spinning and non-spinning reserve. The spinning reserve is generation capacity synchronized to the grid and can be available to dispatch in 10 minutes. Non-spinning reserve is generation capacity not synchronized to the grid but can be made running and available to dispatch in 10 to 30 minutes.

c. Black Start Facilities: in the event of a system-wide outage, i.e. total loss of power, black start units are used to re-energize the system. A typical black start unit is a diesel engine.

2.7 Market Modelling and Bidding in Electricity Markets

Electricity markets can be monopolistic, perfectly competitive or oligopolistic, depending on the market power a participant wields. A perfectly competitive market has many buyers and sellers, with no seller dominating the market. A seller in this market has no distinct advantage over others and accepts price dictated by the market. Power producers typically bid their marginal cost of production. All participants in this market are price-takers [17][27]-[28]. A producer's profit is computed as:

$$\mathrm{p(Q)} = \mathrm{RQ} - \mathrm{C(Q)} \tag{2.1}$$

where Q is the production quantity, R is the market price, p(Q) is the producer's profit from producing quantity Q and C(Q) is the cost of producing quantity Q. To maximize profit, the generator only needs to determine the quantity to produce. Differentiating Equation (2.1) with respect to Q and applying first order condition gives

$$\mathrm{p'(Q)} = \mathrm{R} - \mathrm{C'(Q)} = 0$$

$$\mathrm{R} = \mathrm{C'(Q)} \tag{2.2}$$

Equation (2.2) shows that for maximum profit, the marginal production cost should be equal to the market price. This implies that a generator only needs to dispatch its generating units in a way that incremental production cost is same as the market price. Several studies however, have reported electricity markets to be oligopolistic and not perfectly competitive [26][29]-[30]. This can be due to large capital investment and technology needed in power generation and distribution and transmission constraints and losses which discourages customers from buying power from distant generators. In an oligopolistic market, there are few sellers, hence fierce competition. A power producer with large enough quantity and good bidding strategy would have market power. Exercising this power can be by reducing quantity of power to be produced or increasing offer price for quantity produced [27].

In a competitive electricity market, the main objective of the generator is to maximize its benefits from the market. Profits derived are determined by factors such as level of demand, generator’s bids and bids from competitors. With no power over rivals’ bids and demand for energy, generators take steps to strategically place bids for optimal profits and minimum risk of not being selected to supply. Popular methods for electricity generation market modelling can be grouped into simulation models, equilibrium models and optimization models [31]. Equilibrium models analyse the competitive market considering behaviour and strategy of all power producers. The method applies techniques from game theory to simultaneously maximize profit of each generator competing in the market. Equilibrium models are based on the principle of Nash equilibrium [32], which occurs when no producer can benefit from a change in its bid strategy considering no change in bids of competitors. Equilibrium state would signify point of optimal bids of producers in the market [30]. The Cournot model [28] is an example of equilibrium models, where competing generators base competition on production quantity. Borenstein and Bushnell [33] found the profit-maximizing output of a GENCO by maintaining a constant quantity for others in an iterative process. This calculation is repeated until a state of Nash equilibrium is achieved. The method though has limitations about conditions for convergence. In a similar study, Kian et al. [34] developed a strategy to maximize profit for GENCOs and load serving entities in a supply and demand auction using a feedback Nash-Cournot model. Assumptions made however, included all participants having prior knowledge of competitor’s bid information which is not probable. The Cournot model has been viewed to be more suitable for analysis of market power as seen in [35][36] than for building optimal bids for GENCOs. It is of limited use for inelastic demand and incompatible with the price/quantity competition nature of electricity markets as generators' strategies are based only on production quantity [31][37]. Another example of equilibrium models is the supply function equilibrium (SFE). Klemperer and Meyer [38] introduced the SFE approach, showing a better strategy for modelling uncertainty in electricity markets by relating quantity and price as opposed to the Cournot model (fixed quantity) or Bertrand model (fixed price). This gives a more realistic representation of the behaviour of power producers in an electricity market. The output of the SFE model is a bid curve stating price and corresponding quantity. Green and Newbery [39] applied the SFE model to the England and Wales electricity market for analysis of market power. SFE have some limitations relating to computational complexities as they are represented by differential equations as opposed to algebraic equations found in traditional equilibrium models [31]. To address this limitation, many researchers use a linear form of the SFE model. Green [40] implemented this approach with the case of asymmetric GENCOs in England and Wales electricity market. Baldick et al. [41] extends the application of this model by making some changes in same market to include capacity constraints and affine marginal costs. Likewise, Al-Agtash [42] developed a supply curve bidding approach from a GENCO's perspective based on the SFE model. The approach outputs the profit-maximizing bids from iteratively altering solutions from the SFE model. However, the SFE has some drawbacks that may limit its application. A major drawback is the possibility of producing multiple equilibria with no clarity as to which best defines the GENCO's strategic behaviour [31]. There is also the limitation of computational complexities, increased with the system of differential equations. Solutions to these equations may not follow the non-decreasing curve constraint of a supply function. With SFE model relying on the assumption that slope of the demand function remains constant across time periods, applying the model in situations where transmission constraints are considered may not be feasible [36].

Simulation models also consider strategy of all market participants in analysis of market behaviour. They evaluate the effects of repetitive interaction between market participants for operation and strategic bidding [31]. Otero-Novas et al. [43] presented a model representing profit-maximizing behaviour of market participants under different types of constraints. An iterative procedure was used to simulate market behaviour with participants picking their best response to the market in each iteration. The model was applied to the Spanish electricity market.

In related research, Walter and Gomide [44] suggested a fuzzy-rule based approach to model bidding strategies for power auction and Bower and Bunn [45] presented an agent-based simulation model to examine the behaviour of GENCOs in wholesale electricity market of England and Wales. The model represents GENCOs as autonomous adaptive agents developing their own bidding strategies under constraints in a repetitive daily market, profit-maximizing strategies are obtained based on results from previous market sessions. Simulation models have the advantage of being able to accommodate more complex assumptions over traditional equilibrium models [31]. These models are useful in the analysis of market rules and regulatory measures as general methodology states participants make decisions based on previous experience while adjusting to changes in the environment [31]. Equilibrium and Simulation models concurrently examine profit maximization of each GENCO competing in the electricity market. With the many simplifying assumptions made to apply these models, they are seen to be more suitable for analysis of potential market power and not building optimal bidding strategies as equilibrium point achieved from these assumptions may not be applicable to strategic bidding.

Optimization models presents analysis of strategic bidding by a single firm in the electricity market, the objective function is to maximize profit subject to some technical and economic constraints. Optimization algorithms are applied to provide solutions with these models. Computation flexibility associated with optimization models make them applicable to short-term building of daily bid curves [31]. Wen and David [46] presented a framework for strategic bidding by power producers. The method assumes power producers submits offers as a linear supply function, coefficients of this function are chosen to maximize profit noting offers by competitors and subject to technical constraints. Historical data on bidding is employed to estimate bid coefficients of rivals and analysed to follow a joint normal probability distribution. The optimal bidding problem becomes a stochastic optimization problem with a single objective function subject to some technical constraints. The problem was solved with Monte-Carlo simulation and an optimization-based technique. Effects of symmetrical and unsymmetrical information among power producers present in the market was also included in the analysis. The authors extended this approach of estimating rivals' bid coefficients to the study in [47], integrating two bidding strategies; maximum hourly-benefit and minimum stable output, to develop an overall bidding strategy for GENCOs in the DAM. Stochastic optimization models were used to describe the bidding schemes and genetic algorithm to solve the overall bidding problem. Similar research that model rivals' bidding behaviour was done by Gountis et al. [48], where the optimal bidding problem was modelled as a two-level optimization problem; profit-maximization for GENCOs and economic dispatch by the ISO. The problem was solved utilizing Monte-Carlo simulation and genetic algorithm techniques. Anderson and Philpott [49] presented a model for GENCOs to build optimal supply function offers, representing energy demand and rivals' behaviour with a probability distribution to derive optimality conditions. In a related research, Garcia-Gonzalez et al. [50] developed a method to find optimal bids for a GENCO under market uncertainty. It was assumed that the GENCO had sufficient data on the market to generate rivals' behaviour scenarios through residual demand. Researchers have also applied other heuristic and metaheuristic techniques such as particle swarm optimization [51][52], differential evolution [53][54] and shuffled frog leaping algorithm [55][56] to solve the optimization problem for GENCOs. More literature on optimization models for a single GENCO can be found in [26][57][58]-[59].

This section has attempted to provide a brief discussion on literature relating to market modelling and strategic bidding by power producers. The set of literature reviewed describes solving the strategic bidding problem by some game theory-based approach and estimating rivals' bidding behaviour with a probability distribution and/or residual demand curve facing the GENCO of interest. These techniques rely mainly on access to sufficient data on bidding history in the market. With little information on auction process and bidding history, this thesis explores building a GENCO's optimal offers by estimating the MCP for each hour of the trade day in a DAM, extending this to the SM and incorporating possible risk with uncertainty in demand while acknowledging high prices feature of the SM. The analysis in this thesis examines a method for GENCOs to simultaneously participate in DAM and SM and gain optimal benefits from both markets. This is a short-term analysis, 7 to 14 days prior to the trade day.

2.8 Summary

This Chapter began by describing the ISO and its duties, explaining the process of determining hourly MCPs and settlements within. It went on to outline the operation of some common markets existing in a deregulated power industry, relating how system reliability and security is maintained. The last section presents market modelling techniques and methods suggested by researchers in building optimal strategies for bidding in energy market.

CHAPTER 3

BUILDING OPTIMAL PRICE/QUANTITY OFFERS

3.1 Introduction

The overall aim of this research work is to explore GENCO's participation in electricity markets for optimum market returns. The proposed approach to get desired results detailed in this Chapter models the general problem of obtaining maximum profit from electricity markets as a constrained optimization problem, with MCP as input variable. Since the approach is being implemented for GENCOs with thermal generating units, operating cost in the objective function is described with the fuel cost presented as a quadratic cost function. The first step to solving the GENCO's problem is to estimate next day's prices in the electricity markets. Double seasonal Holt-Winters model, a univariate time series model based on exponential smoothing, is introduced for short-term electricity price forecasting. A brief description of the model and the way it can be applied to prediction of hourly MCPs which have been observed to follow daily and weekly seasonal pattern is presented in this Chapter. With forecast of next day energy market prices as GENCO's offer price, the objective function of the optimization problem is solved for profit-maximizing offer quantity which is the second step of the approach. Hourly price/quantity pairs make up the supply offers submitted in the auction process in electricity markets. The algorithm of the golden section search method utilized to solve the optimization problem will be described in steps. For cost minimization, an economic distribution of load (offer quantity in this case) is done by GENCOs among committed units. This process of economic dispatch would ensure that the GENCO is operating at the least incremental running cost. This is an important part of the optimization problem for proper estimation of expected daily market benefits and economic operation of units. The economic dispatch in this context becomes a subproblem of unit commitment. After determining the offer quantity from the optimization algorithm, the unit commitment process is carried out again for hourly scheduling and subsequently economic dispatch would integrate other operational constraints such as reserve constraint for system security into the optimization process. This Chapter introduces dynamic programming procedure and describes its application for economic dispatch. Economic dispatch of units would form the last step for profit-maximization approach proposed in this thesis. This Chapter relates an approach to achieving the desired results of maximizing profit from supplying energy in electricity markets, a test of the methods with a sample practical utility would be presented in the next Chapter.

3.2 Problem Formulation

The objective of a GENCO is to maximize benefit from the electricity market for each hour of the trade day while minimizing cost. Cost associated with power generation has two components: fixed cost and variable cost. Fixed costs are mostly capital costs, insurance and land related, which are constant irrespective of amount of generation. Variable costs would change depending on the level of production. A GENCO's variable costs consist of fuel cost and operations and maintenance cost [60]. For renewable power generation, operation and maintenance costs have more influence in determining production cost while for thermal power plants, fuel cost dominates with operation and maintenance cost less than 10% of the total variable cost [60]. The model presented in this thesis relates to GENCOs with thermal plants, thus the fuel cost is assumed the production cost to be minimized. If the valve point effect of a thermal power plant is ignored, the fuel cost can be described as a smooth function defined by polynomial functions [61]. The smooth function for fuel cost in an idealized form is expressed as [62]:

$$FC_i(P_i) = c_i + \sum_{j=1}^{L} a_{ji} P_i^j + r_i \tag{3.1}$$

$$i = 1, 2 \ldots M$$

Where FC_i is the fuel cost function of the ith generating unit, P_i is the power output of the ith thermal unit, c_i and a_i are the cost coefficients, r_i is the error related to the ith equation, L is the equation order (1 for linear model, 2 for second-order, 3 for cubic), M is the total number of thermal generating units. c_i would be the value of the cost function when generation output is zero. Since thermal power plants can be represented by quadratic fuel cost functions [63], excluding the error, Equation (3.1) becomes:

$$FC_i(P_i) = c_i + a_{1i} P_i + a_{2i} P_i^2 \tag{3.2}$$

If $b_i = a_{1i}$, $a_i = a_{2i}$

$$FC_i(P_i) = c_i + b_iP_i + a_iP_i^2$$

$$FC_i(P_i) = a_iP_i^2 + b_iP_i + c_i \tag{3.3}$$

The problem of daily benefit for 24 separate hourly auctions is described as:

$$max \sum_{h=1}^{24}\left[p(Q^h) = R^h * Q^h - C(Q^h)\right] \tag{3.4}$$

$$Q^h = \sum_{i=1}^{M} P_i^h \tag{3.5}$$

$$P_i^{min} \le P_i^h \le P_i^{max} \tag{3.6}$$

Where Q^h is the production quantity at hour h, R^h is the market clearing price at same hour, $C(Q^h)$ is the total cost of producing quantity Q^h and $p(Q^h)$ is the profit from producing quantity Q^h. Equation (3.4) presents hourly profit as revenue minus production cost. For optimal benefit, offers to be submitted for the trade day should be decided in a way as to minimize risk of not being selected to supply. Equation (3.4) has two variables; MCP and production quantity. Estimating the MCP would give an insight into the quantity that can be offered at a given price. Solving the GENCO's optimal benefit problem described in this thesis is divided into three sections: MCP prediction, optimization of the objective function and economic dispatch of generating units. The proposed approach is presented by the simplified flow diagram in Fig. 3.1. Equation (3.5) presents the offer quantity Q^h to be the summation of output from each generating unit running at hour h while the inequality constraint in (3.6) is the generating unit's limits constraint. The output of each unit at every interval should be within the range of minimum and maximum possible generation. Units' operating limits are designed to reduce forced outages and improve useful life period.

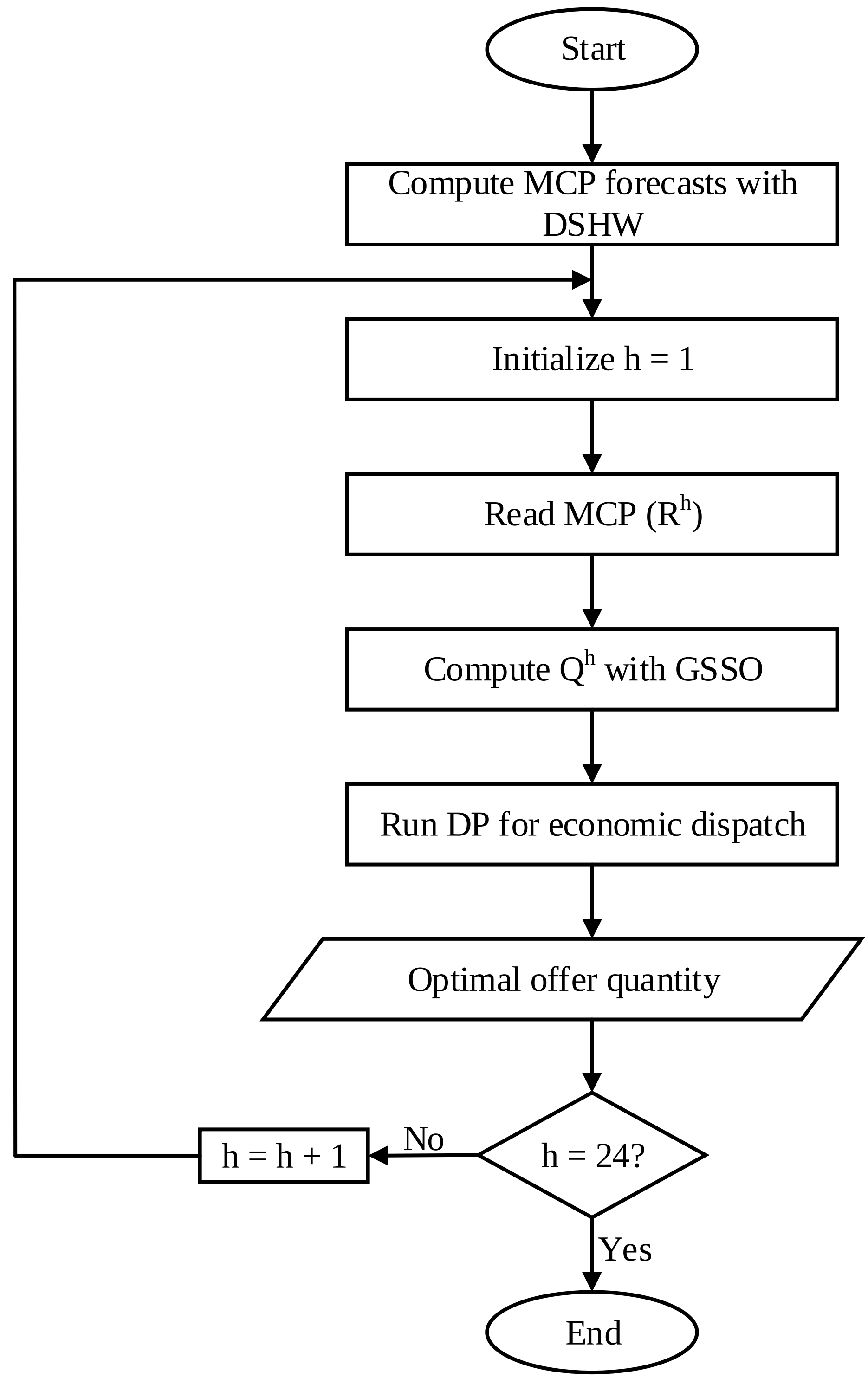

Fig. 3.1 Flow diagram of proposed approach

3.3 Electricity Market Price Forecasting

As was described in the previous Chapter, in a liberalized power industry, power producers submit offers of energy blocks to the market operator, consisting of minimum selling price and quantity to sell. Likewise, retailers and large consumers submit buying bids of energy blocks, with maximum buying prices and quantity. The market operator run an unconstrained dispatch algorithm, offers arranged from the least expensive in an ascending order of increasing price against buying bids ranked in decreasing order of price. The point of intersection defines MCP for each market period, usually one hour. Producer offers with price lower than or equal to the MCP are accepted and producers are scheduled according to their accepted offer. Likewise, consumer bids with price greater than or equal to the MCP are accepted and those consumers are informed of the quantity available to them. MCP is the cost of an additional megawatt-hour of energy and this is the price paid to all GENCOs irrespective of the offers submitted. GENCOs aim at maximizing profit, selling power when prices are high, in a competitive environment and under uncertainties and consumers also look to minimize cost. Thus, market price forecasting is important for market participants.

Electricity market price forecasting is a prediction of the market price of electricity within a timeframe. Depending on area of use, price forecasting can be short-term (few days), medium-term (weeks to few months) or long-term (months to few years). With restructuring of the power industry, electricity has become a commodity to be traded in various markets. Electricity however has some characteristics different from other regular commodities which can affect the application of popular forecasting methods to electricity markets. Examples of such characteristics are problem of economic and efficient storage and possible transmission congestion since there is a requirement of constant balance between demand and supply. Electricity price can thus be very volatile with unusually high or low spikes [64][65]. Generally, factors that affect electricity market price volatility includes availability of inexpensive generation facilities/renewable forms of generation, sudden loss of generation, disruptions in transmission system, volatility in fuel price and weather changes. The manner in which some of these factors affect price volatility however varies across markets in different regions [66]. Short-term electricity price forecasting is employed by GENCOs to determine bidding strategies and setting up bilateral contracts. Retailers and large consumers also make price forecasts for similar purposes. Medium-term forecasting is applied in mid-term planning such as schedule and allocation of resources while long-term forecasting is used for planning purposes which includes capacity expansion analysis. Factors to be considered in electricity price forecasting includes historical demand and forecasted demand, historical price, temperature, day of the week and special days (holidays or special events). Although market information on these factors may be limited, an estimation of the MCP would help a GENCO in determining its optimal offers more precisely as an offer close to the MCP would mean more profit. Forecasting of electricity market prices can be done with simulation-based or analysis-based methods [66]. Simulation-based methods require good knowledge of system operation and access to data on all determining factors, hence they are mostly used by market operators [66]. Analysis-based methods are employed by market participants as they are implemented with observable and historical operation data. Under analysis-based methods, time series models have been used extensively in price forecasting.

3.3.1 Time Series Models

A time series is a set of data points observed over a period in equally spaced intervals [67]. If the observations contained in the series is for a single variable, it is a univariate time series. A multivariate time series has observations for more than one variable. Analysis of time series is done to account for structure and important features of the series while time series modelling considers possibility of having forecasts for future values based on observed values [67]. Past observations are used to build a model which is applied to forecasting of future values. An adequate model needs to be used with a time series to get good forecast results in time series forecasting. A univariate forecasting is employed for complex time series or when there is insufficient data on the process under evaluation. A time series can be discrete or continuous though variable observed in a discrete time series is usually assumed to be a continuous variable [68]. Components read from observed data that can affect nature of time series are described as [69]:

- Cyclical component: this relates to changes in a time series from factors that repeat in cycles.
- Seasonal component: this usually describes variations in a time series that occur within a year.

- Irregular component: this relates to random variations that occur in a time series, following no specific pattern.
- Trend: this is the direction of a time series over a long period of time. Either the series is increasing, decreasing or there is no change.

Autoregressive moving average (ARMA) [70], autoregressive integrated moving average (ARIMA) [71][72], generalized autoregressive conditional heteroskedasticity (GARCH) [73] are time series models that have been implemented in forecasting prices in the day-ahead energy market. The ARMA and ARIMA models are combinations of the autoregressive (AR) and moving average (MA) linear time series models. For the autoregressive model, the process followed assumes that the linear combination of a number of observations from the past, a random error, and a constant, determine the future value of a variable [68]. It is a linear regression of the present value against prior values of the series. In the moving average model, the process involves linear regression of the present value against random errors from past observations [68].

a. Autoregressive Moving Average Model: this is a univariate time series model applicable only to stationary time series. A stationary time series would have its statistical properties remaining unchanged over time. A combination of autoregressive and moving average processes, the ARMA(b, q) model is defined as [68][70][74]:

$$y_t = c + \sum_{i=1}^{b} \varphi_i y_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \qquad (3.7)$$

Where y_t is the current value at time t, c is a constant introduced from the AR model, φ_i is AR model parameter and b is the order of the AR model. ε_t represents random error which is assumed to be white noise, θ_j is the MA model parameter and q is the order of the MA model. [70] describes variations of the ARMA model in its application to electricity price forecasting. ARMA models are easier to manipulate with lag operator notation which moves index back with one time unit; $\mathrm{L}y_t = y_{t-1}$ [74]. Presenting the ARMA model with lag polynomials [74] gives:

$$\varphi(\mathrm{L})y_t = \theta(L)\varepsilon_t \qquad (3.8)$$

$$\varphi(\mathrm{L}) = 1 - \sum_{i=1}^{b} \varphi_i L^i, \theta(\mathrm{L}) = 1 + \sum_{j=1}^{q} \theta_j L^j$$

b. Autoregressive Integrated Moving Average: this is an extension of the ARMA model to accommodate evaluation of non-stationary time series [75]. In the ARIMA model, a difference operator is introduced to make a non-stationary time series stationary. It is a combination of AR parameters, MA parameters and a number of differencing passes. The non-seasonal ARIMA(b, d, q) model using lag polynomials is defined as [6][68][69]:

$$\varphi(\mathrm{L})\nabla^{d} y_t = \theta(L)\varepsilon_t \tag{3.9}$$

$$\left(1 - \sum_{i=1}^{b} \varphi_i L^i\right)(1-L)^d y_t = \left(1 + \sum_{j=1}^{q} \theta_j L^j\right)\varepsilon_t \tag{3.10}$$

where b, d, and q represent the order of the AR, integrated, and MA parameters respectively. d is the level of differencing required to make non-stationary time series stationary and invertible. Thus, a non-stationary time series is known as the integrated version of a stationary time series. A case of ARIMA model commonly encountered is ARIMA(0,1,0), known as the random walk model [74]. The prediction equation for this model is:

$$y_t = y_{t-1} + \varepsilon_t \tag{3.11}$$

Multiplicative seasonal ARIMA is an extension of the ARIMA model for time series with seasonal component. It includes evaluating seasonal parameters for a specified lag, that is, seasonal AR, seasonal differencing, and seasonal MA parameters. The model takes the form ARIMA(b, d, q)×(B, D, Q)$_s$.

c. Generalized Autoregressive Conditional Heteroskedasticity: this is a non-linear time series model. A variation of the autoregressive conditional heteroskedasticity model [76] which is non-linear in variance but linear in mean. This model opposes the assumption of constant variance as found in ARIMA models [77]. The process for the model involves finding a best-fit AR model, evaluating autocorrelation of the error term and testing for significance. GARCH introduced and explained in [78], is suitable for time series susceptible to volatile changes.

The models described are parsimonious stochastic models. The principle of parsimony follows using the model with the smallest number of parameters that provides adequate approximation to the underlying time series data [79]. If there are a number of adequate representations of the series, the simplest option should be used to avoid overfitting. Models with high number of parameters have the risk of overfitting. An overfitted time series model can be unsuitable for forecasting. Other techniques that have been used in electricity price forecasting include artificial intelligence-based models, dynamic regression models, heuristics, wavelength transform models, and Bayesian techniques. Electricity price is a non-stationary process with seasonal patterns, hence a model with seasonal parameters would be better suited for forecasting. In this research work the double seasonal Holt-Winters (DSHW) model, a univariate time series method based on exponential smoothing, is applied to short-term MCP forecasting in electricity markets. It is found to be easy to implement and suitable for short-term forecasting as detailed in the following section. [80] also explains a choice of exponential smoothing model over ARIMA model with the latter as more fitting for series with short-term correlation and not one with seasonal and trend components.

3.3.2 Double Seasonal Holt-Winters Model

Winters [81] introduced the standard Holt-Winters model based on triple exponential smoothing for forecasting seasonal time series. This method is an improvement on the Holt's model of double exponential smoothing, to include seasonality which is sometimes referred to as periodicity. The method has four equations; one forecast equation and three smoothing equations. The smoothing equations represent level, trend and seasonal component [82]. There are two versions of this method depending on the nature of the seasonal component: multiplicative version and additive version. With the multiplicative version, the underlying level of the series is multiplied by the seasonal index while seasonal factors are added to the underlying trend in additive version [83]. The multiplicative version is more suitable in situations where changes in seasonal variations is proportional to the level of the series. The additive version is appropriate if there are no changes in seasonal variations through the series [82]. Since energy price is dependent on factors that include energy demand and level of demand is affected by variations in conditions that determine demand, the multiplicative version is adopted in this thesis.

Extending standard Holt-Winters' method of forecasting seasonal time series with one seasonal pattern, Taylor [83] described a modification of the method to accommodate time series with dual seasonal pattern. The DSHW model as described would have an additional seasonal index and a separate equation for the second seasonal component. The method was implemented for short-term electricity demand forecasting in [83] and was seen to produce favourable results. The approach is extended in this thesis for short-term MCP forecasts. Equations presenting the DSHW method as described in [83] are as follows:

$$L_t = \alpha\left(X_t/\left(DS_{t-p1}WS_{t-p2}\right)\right) + (1-\alpha)(L_{t-1} + T_{t-1}) \tag{3.12}$$

$$T_t = \gamma(L_t - L_{t-1}) + (1-\gamma)T_{t-1} \tag{3.13}$$

$$DS_t = \delta\left(X_t/\left(L_t WS_{t-p2}\right)\right) + (1-\delta)DS_{t-p1} \tag{3.14}$$

$$WS_t = \omega\left(X_t/\left(L_t DS_{t-p1}\right)\right) + (1-\omega)WS_{t-p2} \tag{3.15}$$

$$\widehat{X}_t(k) = (L_t + kT_t)DS_{t-p1+k}WS_{t-p2+k} \tag{3.16}$$

Where t is an index denoting a time period, X_t is the observed value, L_t is the level and T_t the trend. DS_t and WS_t are the first and second seasonality, both with period $p1$ and $p2$. α, γ, δ and ω are smoothing parameters in the range [0, 1]. $\widehat{X}_t(k)$ is the forecast for k hours ahead. The method estimates local slope (trend) by smoothing successive differences between levels. DS_t with period $p1$ is estimated by smoothing the ratio of observed value to the product of level and second seasonality, WS_{t-p2}. Likewise, WS_t with period $p2$ is estimated by smoothing the ratio of observed value to the product of level and first seasonality DS_{t-p1} [83]. MCPs like market demand display daily and weekly seasonality. Applying the method to hourly MCP forecasting in electricity market, DS_t and WS_t would represent daily and weekly seasonality respectively. $p1$ is thus set to 24 and $p2$ to 168. Historical day-ahead auction MCPs from Nord Pool is used in the model, actual and forecast values for the week January 1st to January 7th, 2017 are shown in Fig. 3.2. The DSHW method is a robust univariate time series method that can be used for online short-term MCP forecasting, its application is less demanding compared to other time series models.

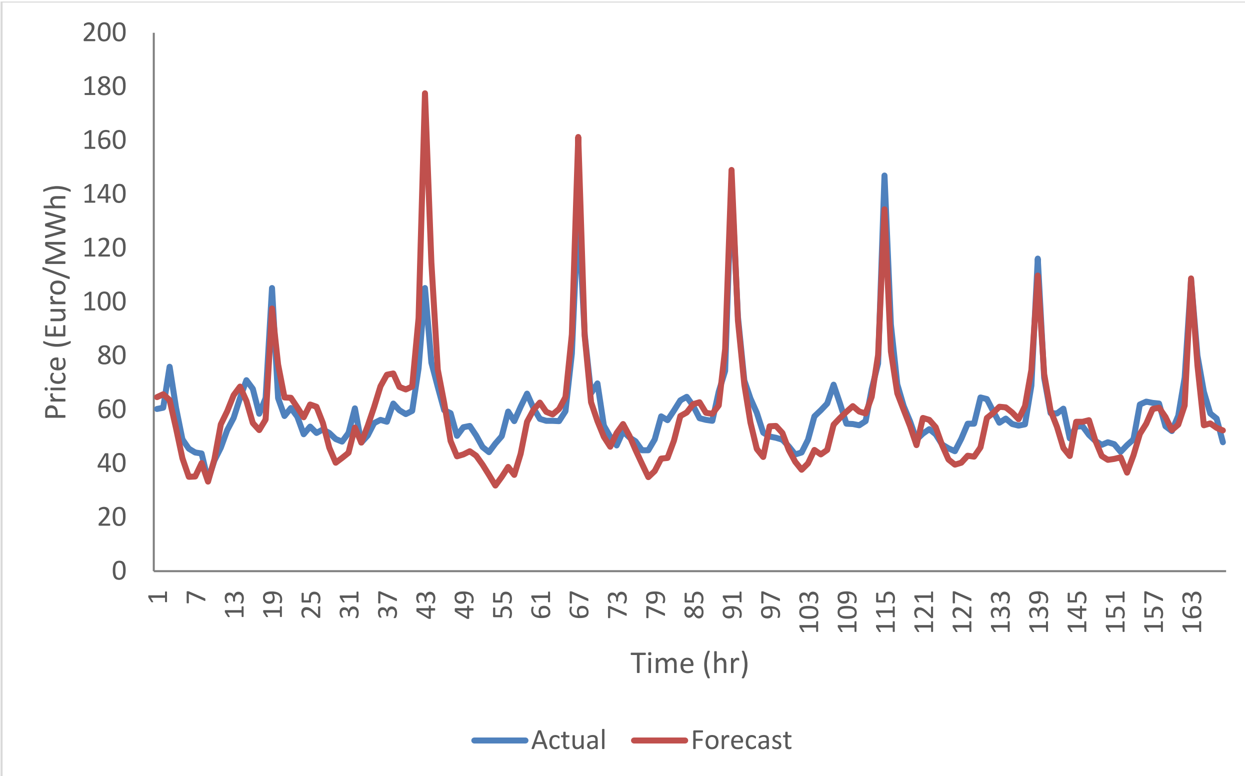

Fig. 3.2 One-week Nord Pool real and simulated day-ahead auction MCP with DSHW model

With the requirement of electricity demand and supply being balanced at every interval, a large increase in demand or decrease in supply can lead to price spikes. Contributing factors to this volatility can be LFU or load under-forecast, error in output forecast of non-dispatchable generators and bidding behaviour of market participants. Effect of spikes on model accuracy is tested by removing data points identified as spikes. Spike data are defined as values greater than $\mu+3\sigma$ or less than $\mu-3\sigma$. The measured error is reduced with points as shown if Fig. 3.3 and Fig. 3.4. Fig. 3.4 gives a clearer picture of difference when the spike data points are removed from a forecast of 48 hours ahead.

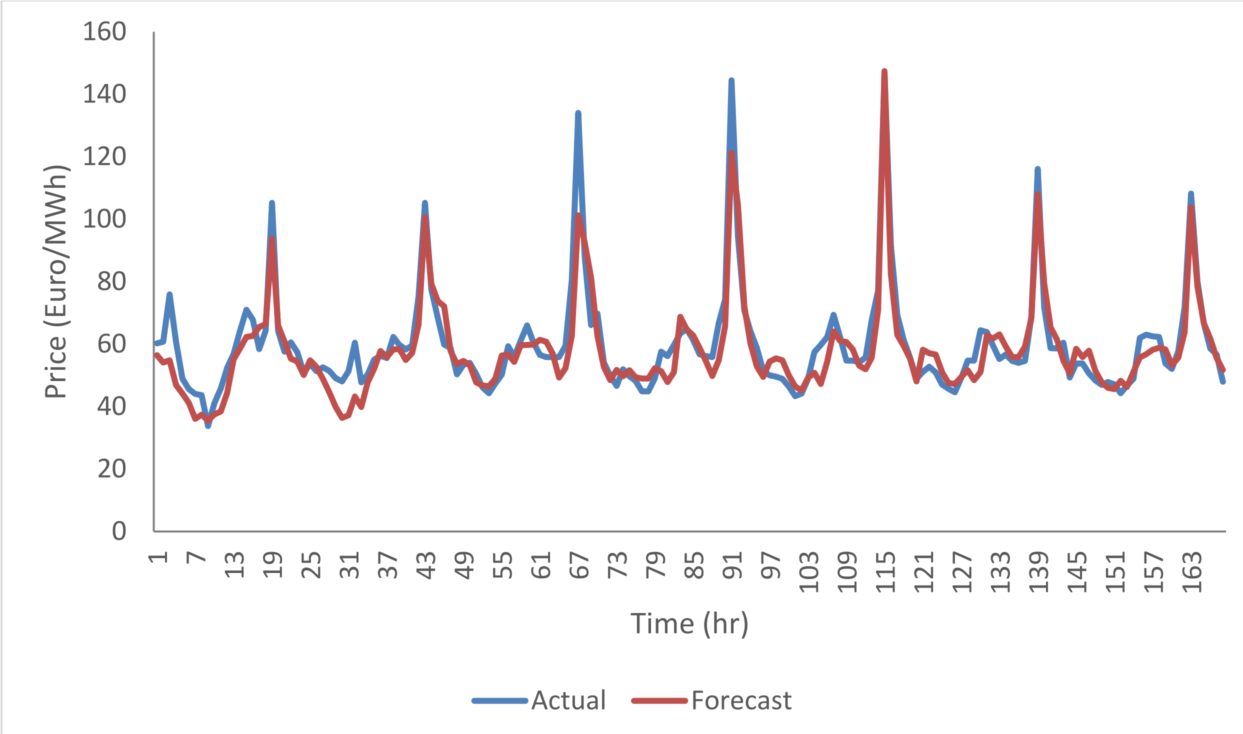

Fig. 3.3 One-week Nord Pool real and simulated day-ahead auction MCP with DSHW model (with spike data points excluded)

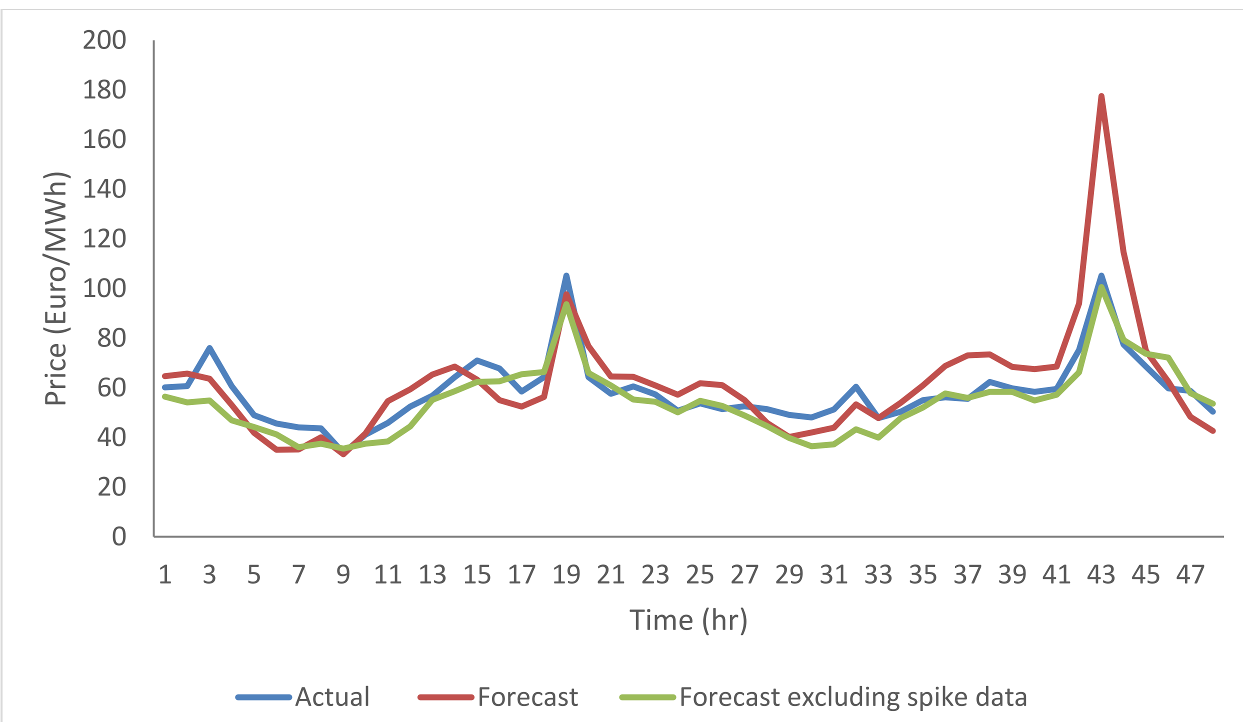

Fig. 3.4 48-hours Nord Pool real and simulated day-ahead auction MCP with DSHW model

3.4 Optimization Algorithms

Main objective of solving optimization problems is to determine the value of one or more decision variables that solve an objective function subject to equality and/or inequality constraint(s). The presence of constraints makes the problem a constrained optimization problem. Optimization problems can also be defined without constraints, these are referred to as unconstrained optimization problems. Optimizing the objective function would mean finding the function’s maximum or minimum. Optimization problems can be linear, quadratic, or non-linear, depending on the nature of the equations. They can also be deterministic or stochastic, continuously differentiable (smooth) or non-differentiable, and the decision variables may be continuous or integer values [84].

Techniques for finding the best possible solution have been developed and applied in a wide variety of fields such as mathematics, statistics, engineering, computer science, economics, and operations research where optimization problems may occur [85]. These techniques can be broadly grouped as exact algorithms and approximate algorithms. Exact algorithms involve implementing an exhaustive search with the guarantee of a precise optimal solution while approximate algorithms provide suboptimal solutions with provable quality of output [86][87][88]. Exact algorithms are usually the first choice and are readily applied to simple, small-scale problems where effort applied to solving the problem is on polynomial increase with problem size. Effort refers to the computation time and space in the computer memory used by a method. Applying these methods to some practical problems may however prove infeasible. Many combinatorial optimization problems are computationally intractable, which means no exact algorithm has been able to solve them. If an exact algorithm is proposed to solve such problems, then the NP-complete (non-deterministic polynomial time) state of such problems would revert to being solvable in polynomial time with respect to problem size which is a feature of exact algorithms; P = NP [89]. Exact algorithms can be simplex and interior-point methods, complete search algorithms, or problem specific such as the Dijkstra’s algorithm for shortest path in a graph and dynamic programming algorithm for knapsack problems [86]. The methods find the solution to a problem by dividing original problem into subproblems and combining solutions from these subproblems. Approximate algorithms [90][91] are applied to solving intractable combinatorial optimization problems. Similar methods used for computationally tractable problems can also be applied as approximate methods to find suboptimal solutions in computationally intractable problems [87]. These include local search algorithms, sequential algorithms, dynamic programming, and linear programming and relaxation-based algorithms. Some traditional methods for mathematical programming or optimization [84][92][93] are described below. The method to apply when solving optimization problems depend largely on the nature of the problem.

a. Simplex Algorithm: this is an iterative procedure using slack variables and base variables. It analyzes a set of basic feasible solutions in sequence such that with each new solution, the problem of optimizing the objective function improves or remain unchanged. It is a popular method for solving problems in linear programming. Linear optimization problems have linear objective function with linear equality and/or inequality constraints.
b. Method of Lagrangian Multipliers: this method creates a Lagrangian function from the objective function by including the constraints and a new variable called the Lagrange multiplier. The function is optimized by methods of differential calculus. The method is considered for problems with equality constraints. Slack or surplus variables may have to be introduced to have constraints take equality form. The method can be extended to quadratic programming where the objective function is a quadratic function and the constraints are linear.
c. Steepest Ascent Method: this is one of the variations of the gradient search methods. It is sometimes referred to as gradient ascent method and is applicable when the objective function is differentiable and strictly convex. It iteratively finds the maximum of a function based on its first derivative, moving along a path of maximum increase. A similar method is the steepest descent or gradient descent method which finds the minimum of a function.
d. Newton's Method: this method uses the first and second derivative of the objective function. The objective function is approximated by a quadratic function whose coefficients are determined from the objective function and its derivatives. Solution to the optimization problem is obtained by iteratively optimizing the quadratic function, with the solution from a step used as the starting point of the next step. This is typically for optimization problems with one variable. However, the Newton's method can be extended to functions with more than one variable.

e. Branch and Bound Algorithm: the method iteratively creates subsets from a feasible region of solutions. These subsets are checked for optimal solution against some criteria and the search space is narrowed until an optimal solution is found. This approach is particularly applicable to integer programming problems.

The dynamic programming algorithm is also a popular approach and would be discussed later in this Chapter. Heuristic techniques are estimations that can be used when traditional approximate approaches are difficult to implement [87]. These methods exchange the guarantee of optimality for a faster solution, providing a quality suboptimal solution. Heuristic techniques can be broadly grouped into constructive algorithms and local search algorithms [94][95]. Metaheuristics are problem-independent techniques applied for developing heuristic optimization algorithms. Procedure followed takes the form of local search or imitation of a natural process such as biological evolution. A general characteristic of heuristic optimization techniques is that solving the optimization problem usually starts with an initial random guess of the solution, some criteria is set for iteratively generating and evaluating new solutions and the best result is given as the output. The usual stopping conditions for the iterative search are: an acceptable solution has been found, a parameter within the algorithm stops its execution, no improvement in solution after a specified number of iterations, or a specified CPU time has been reached. Some heuristic optimization techniques that have been applied to optimization problems includes [92][94][95]:

a. Simulated Annealing: a method based on the annealing process of solids, it is a metaheuristic for global optimization. It considers one solution at a time which is adjusted by a probabilistic rule in an iterative process until it reaches its optimum.
b. Swarm Intelligence: involves a large number of agents communicating with one another and their environment. The collective experience of these agents is used to generate new solutions. Examples of metaheuristics from this class are the ant colony optimization and particle swarm optimization. The ant colony optimization algorithm is a probabilistic method that mimics the way ants search for food and find their way back to their nest.
c. Evolutionary Algorithm: a population-based metaheuristic, it involves having the entire population modified at the same time. New solutions are generated from evaluation of some defined fitness function. Popular examples of evolutionary algorithms are genetic algorithm and differential evolution.

The shuffled frog-leaping algorithm, a memetic meta-heuristic, has also been applied to solving optimization problems across varying fields [55][96][97]. Some features that can be used for comparisons between heuristic techniques [92] include the procedure for generating new solutions, management of new solutions, number of search agents, ease of implementation, speed of convergence, search space restrictions, methods with specific constraints, and reliability of the method. The golden section search method, a direct search technique, is used in this research work to solve the optimization problem as defined in Equation (3.4) from section 3.2. The approach is found to adequately represent the nature of the optimization problem. Equation (3.4) describes a one-variable optimization problem with the constraint defined in Equation (3.6) as a boundary for the solution search. The technique is relatively easy to implement with a guarantee of convergence and optimum solution.

3.4.1 Golden Section Search Optimization

The Golden Section Search Optimization (GSSO) is a method used to find the maximum or the minimum of a unimodal function. The function would be continuous over an interval. Assumption made in implementation is that the objective function f(x) can be evaluated for x but the derivative of the function is not available [98]. It is similar to the bisection method for finding roots of an equation, but with 3 sections. The interval is divided into 3 sections by adding 2 points between ends. The function is evaluated at the 2 new points, comparing function values to narrow the interval. For an optimal search and less function calls, a constant reduction factor is introduced. Considering a maximization problem, if functions covers the interval [m, n], with two new points x1 and x2 introduced between m and n. Evaluating f(x1) and f(x2): if f(x1) > f(x2), the maximum is between [m, x2]. If f(x1) < f(x2), the maximum is between [x1, n]. The new interval is again divided into 3 sections and evaluation with comparison repeated, until the distance between interval is sufficiently small. The points x1 and x2 are selected in a way that the distance between them and the ends of the search region is equal to the golden ratio [99]. This ratio is the reduction factor.

$$\text{Golden Ratio, GR} = \frac{-1+\sqrt{5}}{2} \tag{3.17}$$

The GENCO's maximum benefit problem as described by Equation (3.4) as objective and Equation (3.6) as constraint can be solved with the GSSO method as shown in the following steps:

Step 1: Initialization

a) Read input data a_i, b_i, c_i (cost coefficients of generating units), P_i^{min}, P_i^{max} (units' generating limits), R^h (predicted prices).
b) Read GR as defined by Equation (3.17).

Step 2: Iteration

a) Assign P_i^{min} and P_i^{max} as the boundaries [m, n].
b) Determine two internal points x1 and x2 such that

$$\mathrm{x1} = \mathrm{m} - \mathrm{d}$$

$$\mathrm{x2} = \mathrm{n} + \mathrm{d}$$

$$\text{where } \mathrm{d} = \mathrm{GR} * (\mathrm{m} - \mathrm{n})$$

c) Evaluate p(x1) and p(x2) using Equation (3.4), Q as x1 or x2

If p(x1) > p(x2)

$$x_{max} = x1$$

$$\mathrm{diff} = 1 - \mathrm{GR} * \mathrm{abs}\left(\frac{m-n}{x_{max}}\right)$$

If diff > ε (a sufficiently small number)

$$\mathrm{m} = \mathrm{x2}$$

$$\mathrm{x2} = \mathrm{x1}$$

$$\mathrm{d} = \mathrm{GR} * (\mathrm{m} - \mathrm{n})$$

$$\mathrm{x1} = \mathrm{m} - \mathrm{d}$$

If p(x1) < p(x2)

$$x_{max} = x2$$

$$\mathrm{diff} = 1 - \mathrm{GR} * \mathrm{abs}\left(\frac{m-n}{x_{max}}\right)$$

If diff > ε (a sufficiently small number)

$$\mathrm{n} = \mathrm{x2}$$

$$\mathrm{x1} = \mathrm{x2}$$

$$\mathrm{d} = \mathrm{GR} * (\mathrm{m} - \mathrm{n})$$

$$x2 = n + d$$

Step 3: Output x_{max}

Step 4: Offer Quantity

a) Repeat step 2 and step 3 for each generating unit.

b) Sum x_{max} from all units to obtain maximum quantity Q^h for the interval.

An example using a GENCO with two thermal generating units whose cost coefficients and generation output limits are listed in Table 3.1, is used to demonstrate this method. Since the generating limit constraint states the output of each unit should be within its maximum and minimum generation capacity, these limits are set as the boundaries of the optimum solution search. Thus, for units 1 and 2 the search interval is [80, 190] and [94, 375] respectively.

Table 3.1 GENCO's generating units' data

Unit	a_i	b_i	c_i	P_{max} (MW)	P_{min} (MW)
1	0.00942	8.1817	369.03	190	80
2	0.00569	12.796	654.69	375	94

Assuming an estimated electricity price of 17.05 \$/MWh, production quantity of each unit is calculated using Equation (3.4) as described in step 2 of the GSSO algorithm. For the first division and search, function maximum, x_{max}, is 148 MW for unit 1 and 267.7 MW for unit 2. After further divisions and evaluations, reducing the distance between intervals till a pre-set tolerance of 10^{-8} between the previous and current values (37 iterations for unit 1 and 59 iterations for unit 2), the function maximum occurs when the output of the units are 190 MW and 373.6 MW respectively. At these production levels, the generating units are operating at a capacity that gives the maximum returns considering the price stated. The GENCO can thus offer to supply 563.6 MW of energy at 17.05 \$/MWh which would be the profit-maximizing offer for the period under consideration. Since unit 1 is operating at the maximum generating capacity, an increase in estimated price would have no effect on its output. There can however be increase in profit due to general increase in revenue with same operating cost. An increase in the price could mean an increase in the output of unit 2. Likewise, a decrease in price would affect estimated profit-maximizing outputs from both units. Taking energy price to be 16.80 $/MWh for example, unit 1 still has its generation at 190 MW but unit 2's output decreases to 349.7 MW. It is important to note that the optimization process only follows generating units' constraints, other operational constraints such as spinning reserve requirement is ignored at this point. This would be further discussed in the next Chapter.

3.5 Dynamic Programming for Economic Dispatch

An essential aspect of power system planning and operation is the ability to provide adequate generation to satisfy demand at minimum cost. Generation end of a typical power system is an amalgamation of different generating units with varying associated cost, incremental operation (fuel cost) and maintenance cost and fixed cost. Economic dispatch is the operation of committed generating units (unit commitment) to supply power such that demand, and other operational constraints are satisfied at minimum cost. The economic dispatch of generating units is an optimization problem where the objective is to minimize running cost subject to level of demand, reserve constraints and operational limits of generation and transmission facilities. In a restructured power system, an ISO is responsible for economic dispatch to minimize energy cost. The ISO run an unconstrained dispatch algorithm to determine the MCP and unit commitment schedule based on demand forecast for the trade day. A constrained algorithm is run to dispatch units in an economic order, recognizing units' ramp rate, generation limits and other characteristics as indicated by GENCOs in the offer submission, losses, and transmission line capacity [10]. Integrating constraints and uncertainty in scheduling dispatch is important in maintaining system reliability. For the ISO to effectively minimize cost, adequate and accurate information from market participants and entities is needed. Frequent run of dispatch algorithm (every 5 minutes by IESO) would also contribute to cost minimization.

A GENCO also solves its economic dispatch problem when making offers in electricity markets, in a similar method to regulated power systems. The optimal operation of units would give a price/quantity pair of offers for profit maximization. General idea behind economic dispatch is to have the unit with the lowest marginal cost being dispatched first. If the unit reaches its maximum generating limit before demand is met, the next cheapest unit is dispatched. This order continues until demand and other system conditions such as transmission loss are met. Economic dispatch algorithm is based on running cost of units which would be fuel cost for thermal units, not fixed cost. If a GENCO has a priority list for M generating units, the objective is to minimize total running cost FC_T subject to equality constraint of sum of power generated should be equal the demand. If transmission losses or reserve requirements are considered, the constraint would be sum of demand and other factors. The problem can be explained as:

$$min\ FC_T = \sum_{i=1}^{M} FC_i(P_i) \tag{3.18}$$

where $FC_i(P_i)$ is fuel cost of unit i as defined by Equation (3.3) and at time h, FC_T would be equal to C(Q) in Equation (3.4). The minimization problem is subject to the generating unit's limits constraint (the output of each unit should be within its minimum and maximum limits) as described in Equation (3.6). Other constraints include:

- Power Balance: to maintain system reliability, total generation should be equal to demand, P_D.

  $$P_D - \sum_{\mathrm{i=1}}^{\mathrm{M}} P_i = 0 \tag{3.19}$$

  Including transmission loss, the above equation becomes

  $$P_D + P_{\mathrm{loss}} - \sum_{\mathrm{i=1}}^{\mathrm{M}} P_i = 0 \tag{3.20}$$

- Ramp rate: adjusting a unit's output between two operating periods can be restricted by unit's ramp rate. If the output of a unit is required to change within the period, the rate of change should be in the range of the ramp rate limits.

  If unit's output is to be decreased,

  $$P_i^0 - P_i \leq RD_i \tag{3.21}$$

  If unit's output is to be increased,

  $$P_i - P_i^0 \leq RU_i \tag{3.22}$$

  where P_i^0 is the previous output power, RD_i is the ramp-down limit and RU_i is the ramp-up limit, of unit i. Combining Equations (3.6), (3.21) and (3.22) gives,

  $$\max\ (P_i^{min}, P_i^0 - RD_i) \leq P_i \leq \min\ (P_i^{max}, P_i^0 + RU_i) \tag{3.23}$$

The economic dispatch problem assumes a number of units have been committed to supply at the required time interval and finds the optimum generating point for each unit. It is a subproblem of unit commitment. The unit commitment problem is solved to find the combination of units that would satisfy demand at minimum operating cost and may be executed as a daily or a weekly problem [14]. Techniques to solve economic dispatch problem for thermal units include the lambda-iteration method, gradient method, dynamic programming, artificial intelligence-based methods and heuristic and metaheuristic algorithms.

Dynamic programming (DP) introduced in [100] is a search method for optimization problems with solution arising from a sequence of decisions. The general working principle of DP [101] is to divide the original problem into smaller and simpler subproblems with search for solution starting from the smallest subproblem. To avoid repetitive calculation in solving current optimization problem and others that might be closely related, a table of results of all subproblems can be created in DP. Optimum solution for each subproblem is saved in the table for future computation or use. A solution to the original problem is achieved by combining solutions of the subproblems, in increasing size from the least. DP process involves making decisions on solutions that depend on some defined optimality criteria. This principle of optimality [102] describes an optimal decision as one obtained from optimal sequence of results which are based on the nature of result of the first decision. A solution to an optimization problem is optimal only if solutions of its subproblems are optimal.

Applying DP to economic dispatch problem is similar to solving a shortest path problem. It would mean finding optimum output of generating units within a system for all possible load levels with units' generating limits as constraint. The exhaustive search and storing partial solutions for future references makes DP a flexible technique for solving the economic dispatch problem.

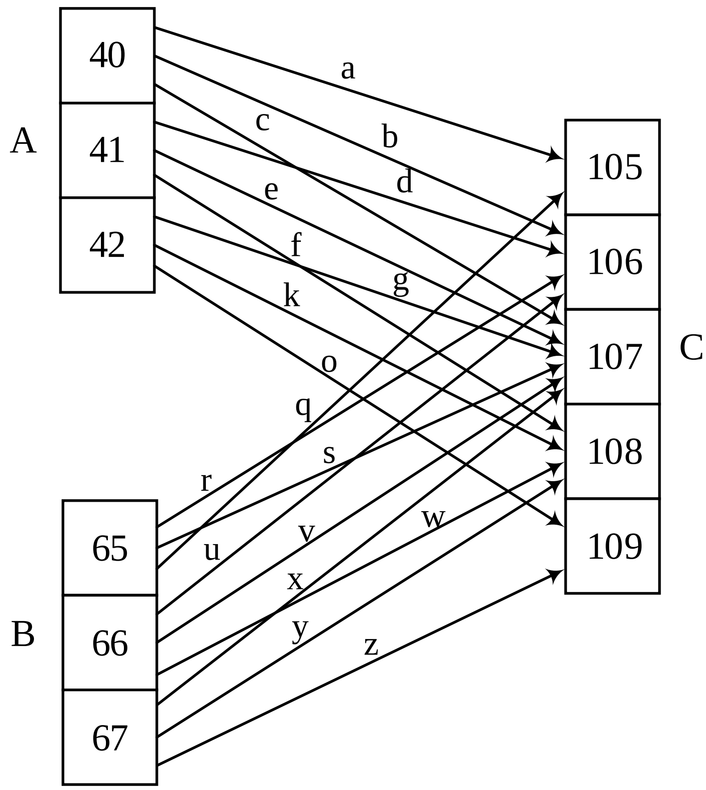

Fig. 3.5 Economic dispatch with DP example

A simple generating facility with two generating units, A and B is used to explain the basic principle of the DP process as shown in Fig. 3.5. Assuming unit A has generating range of 40 MW to 42 MW and unit B has a range of 65 MW to 67 MW, possible load levels that the system can supply would be from 105 MW to 109 MW. Suppose generation from each unit is adjusted with discrete steps of 1 MW (lstep = 1) with a to z representing the running cost for each state as shown in the figure. The DP process evaluates the cost of generating enough output to meet each load level, storing the unit combination with the minimum operating cost. For load levels 105 MW and 109 MW, evaluating the running cost is quite clear since the utility would be producing at minimum or maximum capacity to satisfy each load. Load demand that fall between these two boundaries would however require evaluation of two or more unit combinations to check which has minimum cost of operation. Fig. 3.6 shows a flow chart to illustrate DP process for the economic dispatch problem solved in this research work.

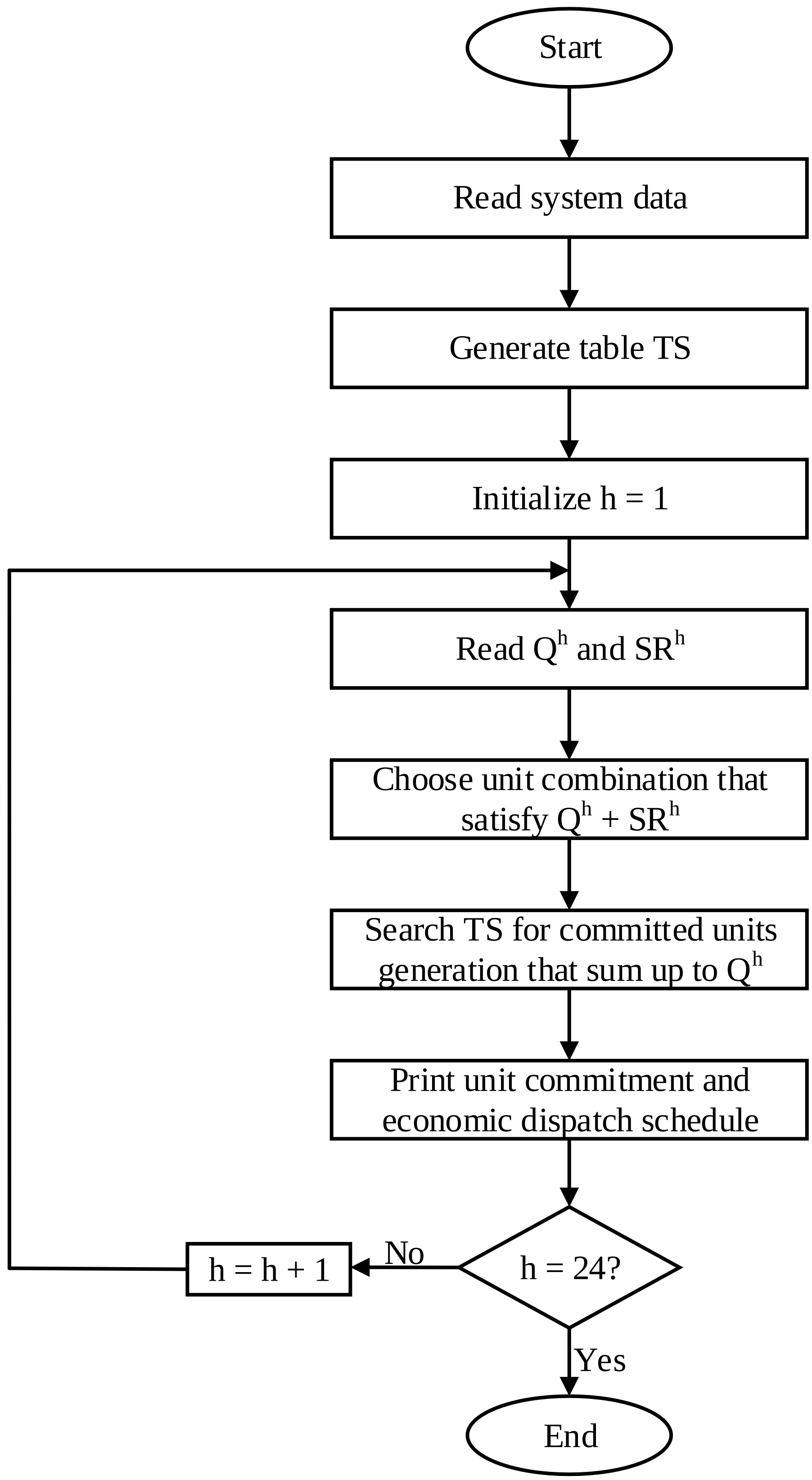

Fig. 3.6 Flow diagram of DP procedure for economic dispatch

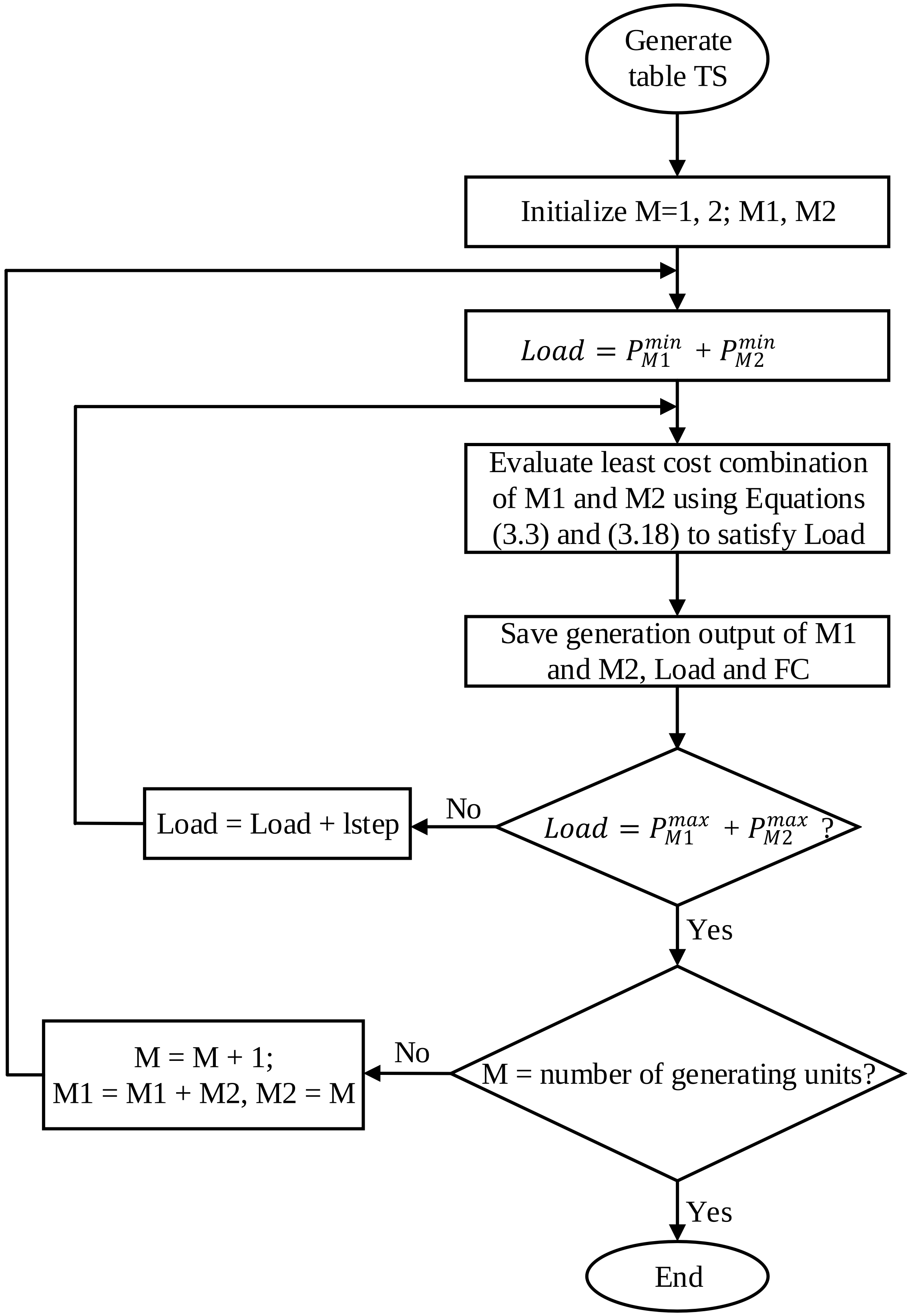

Fig. 3.7 Flow diagram of DP procedure

Fig. 3.7 presents steps to generate table TS. Evaluation of all unit combinations and determining least cost of satisfying possible load levels is done in a table format. Table TS represents a 'look-up' table for all optimal unit combinations and load levels the system can serve. Units' outputs and load levels in this research work are presented in discrete form using step size lstep = 0.1. Hourly optimal dispatch of units is found by tracing a path of minimum cost from the end of an evaluation which is the total load level to be satisfied back to the beginning.

3.6 Summary

This Chapter has described approach proposed in this thesis to solve a GENCO's problem of making profit-maximizing offers in electricity markets. It started with a mathematical formulation of the GENCO's problem as an optimization problem and solution process listed in steps: MCP prediction, estimation of offer quantity with an optimization algorithm, economic dispatch of units. Electricity price forecasting is discussed and application of DSHW model to short-term MCP forecasting was explained. With estimated MCP as input variable in the objective function, associated offer quantity can be obtained with GSSO algorithm as described. The DP procedure for dispatch of generating units as to minimize fuel cost was also described in this Chapter.

CHAPTER 4

OPTIMAL BIDDING IN DAY-AHEAD AND SPOT ENERGY MARKETS

4.1 Introduction

The steps in the proposed approach to solving a GENCO's optimal participation in electricity market problem as discussed will be tested in this Chapter with a sample practical GENCO consisting of twelve generating units. Forecasts of MCP for a trade day are computed. A range of scenarios will be considered for profit-maximizing supply offers in the DAM and SM. SM being a market operating in real-time have higher prices than the DAM auction. This can be due to short time frame between the trade process and supply/delivery of agreed generation quantity. More expensive units are also usually operated to supply energy for the SM. Two situations that can affect nature of offers which should be considered in the decision process will be introduced in this Chapter. First would be the effect of SR which is a capacity allocation for GENCO's system security. Having some capacity on reserve is important for a reliable operation of the system. However, maintaining a reserve requirement would increase operating cost of the facility. Accurate scheduling of reserve and increment in cost should thus be considered in supply offers and balancing between both markets. The other factor to be considered is the effect of LFU. Variability in demand forecast affect actual quantity of energy generation needed on the trade day which in turn affect market prices. LFU is also what determines quantity of demand to be satisfied by the SM.

4.1.1 Load Model and Test System

The unit commitment process for GENCOs reported in this thesis is based on an hourly approach integrated with economic dispatch. It is assumed that the GENCO already has its generating units in a priority list arranged from the cheapest to the most expensive to run. A test system consisting of twelve thermal generating units of different sizes [103] is used to demonstrate the proposed approach. Total system maximum and minimum capacity are 3450 MW and 1166 MW respectively. The priority order, fuel cost coefficients and generating limits of each unit are shown in Table 4.1. Transmission loss is neglected within the GENCO's system. Other constraints such as units' ramp rates, minimum up time and minimum down time are ignored at this point. Effects of transmission congestion/line capacity are also not considered. The utility's commitment is thus based on maximizing benefit with maximum possible capacity as determined by hourly demand since transmission loss is excluded.

Table 4.1 Data for test system

Unit ID	Loading Order	a_i	b_i	c_i	P_{max} (MW)	P_{min} (MW)
10	1	0.03073	8.336	170.44	80	40
11	2	0.02028	7.0706	309.54	120	60
6	3	0.01142	8.0543	222.33	140	68
1	4	0.00942	8.1817	369.03	190	80
4	5	0.00357	8.0323	287.71	300	110
12	6	0.25098	13.052	1207.8	70	20
5	7	0.00605	12.908	722.82	300	130
3	8	0.00313	7.9691	647.85	500	220
2	9	0.00515	12.986	635.2	375	94
7	10	0.00569	12.796	654.69	375	94
9	11	0.00708	9.1575	1728.3	500	125
8	12	0.00421	12.501	913.4	500	125

The trade day considered in this thesis has forecast load profile shown in Fig. 4.1. This is usually made publicly available by ISOs and is estimated days prior to the trade day, making necessary adjustments in forecasts as needed before actual day. Having this information is important for proper planning and offer scheduling by GENCOs. The profile shown represents 24-hourly demand for a typical day in winter in Ontario's electricity market.

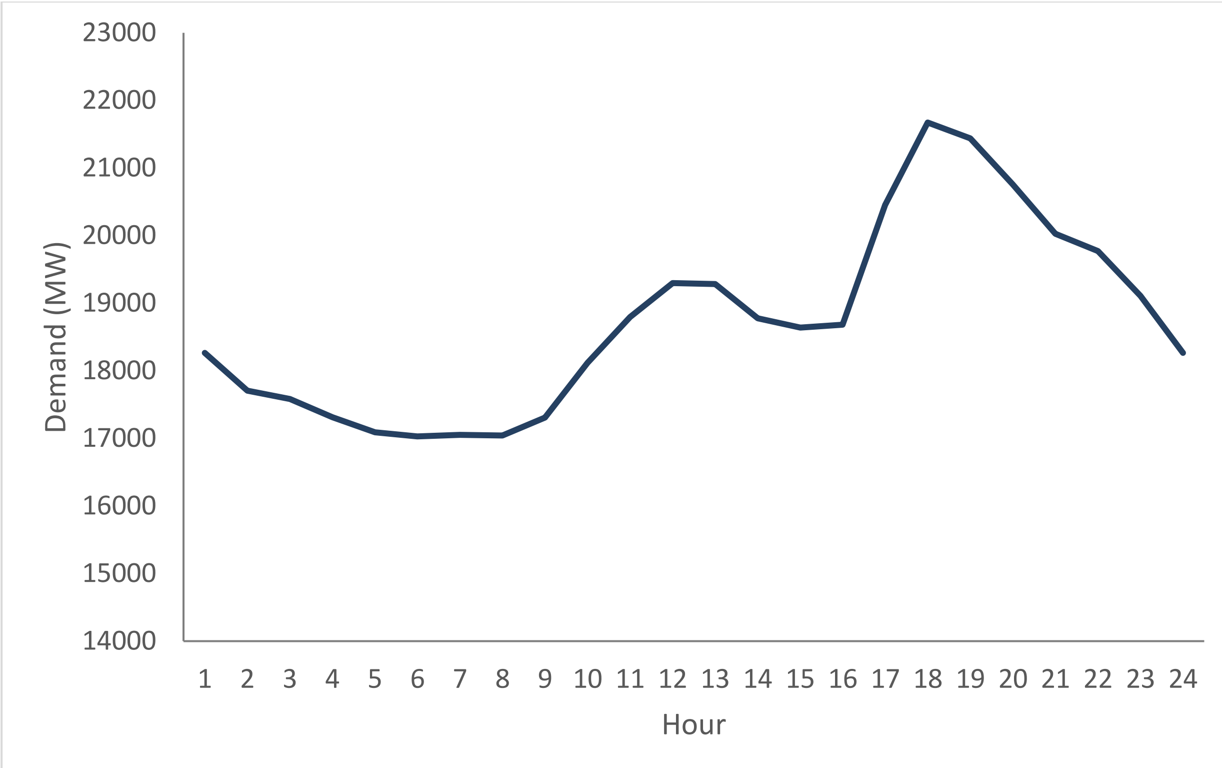

Fig. 4.1 Demand forecast for the trade day

4.2 Bidding in Day-ahead Market

As described in the previous Chapter, the first step of the proposed approach to maximizing a GENCO's market benefits is to estimate hourly MCPs for the trade day. The DAM typically opens up to 7 to 10 days prior to the trade day and closes a day before the trade day. Competing GENCOS submit offers to supply consisting of price and quantity pairs, stating the time offer is available for dispatch. Price prediction done is thus on a short-term basis, estimating the clearing price for energy in the DAM auction for the trade day which is determined in short intervals by an ISO from offers to supply and demand bids. Price predictions made are marked as offer price for maximum benefit and used as input in the optimization algorithm to determine offer quantity. A good estimate of the MCP would limit risk of the GENCO not being scheduled to dispatch and return maximum benefits from market participation. GSSO method described in Section 3.4.1 is applied at this point to estimate the corresponding profit maximizing quantity for each hour of the trade day. The search interval used in the GSSO algorithm is represented by the maximum and minimum generating limit for each unit with the objective function as maximizing result of revenue minus operating cost. Table 4.2 lists the price/quantity hourly offer pairs from the

GENCO at the DAM auction process, minimizing cost at each hour. Quantities from the GSSO algorithm is seen to be high at points where prices are high which follows the economic principle of higher price relates to higher supply quantity. From hour 4 to 5, with a lower estimated price comes a decrease in offer quantity while at hour 22 GENCO is offering all its capacity as estimated MCP is high.

Table 4.2 Profit-maximizing hourly price/quantity offers

Hour	p ($/MWh)	Q (MW)
1	23.04	3380
2	36.64	3380
3	45.85	3380
4	30.88	3380
5	14.36	1330
6	14.33	1330
7	14.35	1330
8	14.36	1330
9	14.31	1330
10	14.33	1330
11	21.87	3380
12	30.18	3380
13	28.99	3380
14	14.35	1330
15	14.85	1330
16	29.66	3380
17	37.55	3380
18	38	3380
19	37.86	3380
20	37.79	3380
21	42.72	3380
22	64.47	3450

23	45.4	3380
24	35.72	3380

Making these offers during the DAM auction would give the profit presented in Fig. 4.2. The operating cost which is total fuel cost of units running to produce offer quantity is deducted from the revenue. At hour 22 where MCP is at the highest, the revenue increases and despite the increase in offer quantity which would raise the operating cost, there is a surge in benefits from supplying at that hour. Market returns are seen at the lowest between hours 5 and 10 and hour 14, where the MCP is low. Increasing offer quantity above what is estimated to be scheduled at that price would result in the GENCO operating at a loss.

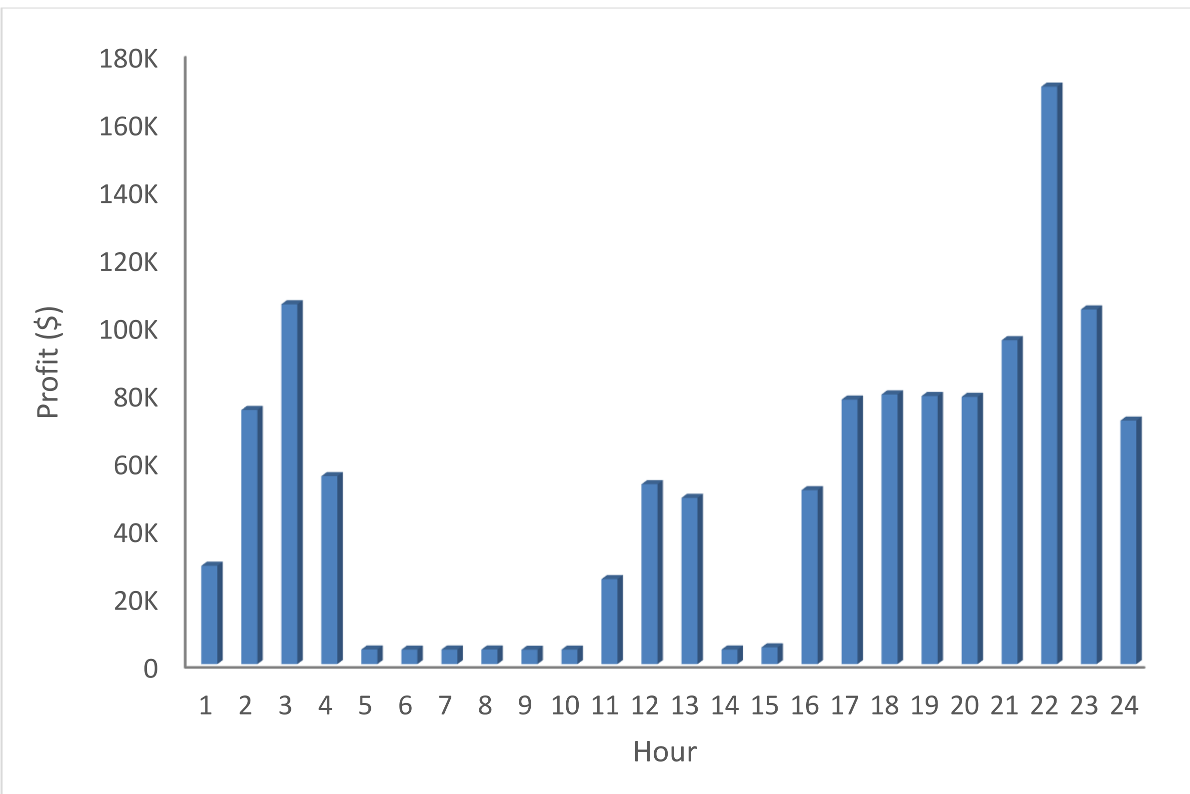

Fig. 4.2 GENCO’s benefits from DAM auction process

4.2.1 Effect of Spinning Reserve for Security

When ISO decides on dispatch schedules for the trade day, GENCOs scheduled are under obligation to make allocated generation available and supply as stated by dispatch schedule/instructions. Inability to deliver scheduled supply would attract fines; GENCOs pay for undelivered power. To plan for unforeseen events such as sudden loss of generation that could cause the GENCO to fall short with scheduled supply, a method of risk assessment is incorporated in the decision process for making offers. Risk is estimated by the probability of the system not satisfying the load [104]. The unit commitment risk which is associated with having enough online capacity to meet demand at a given period of time is evaluated in this research work. For each hour, some quantity of SR is designated through a probabilistic method as reserve capacity to accommodate contingencies. As previously stated, SR is generating capacity that is synchronized to the system and ready to supply load within a few minutes. In regulated environments, some utilities use deterministic criteria such as a fixed percentage of system load, fixed capacity margin, with the most commonly used being largest online generating unit, to deduce reserve requirements. Although easy to implement, it has been shown that these deterministic methods do not properly represent the stochastic nature of system load and other system parameters [4][105]. They can be inconsistent, uneconomic and unreliable by overscheduling or not having enough capacity on reserve [4]. These shortcomings are important considerations in a competitive environment.

The PJM method [106] is the probabilistic technique employed in this research work. The method is based on calculating probability of online generating capacity supplying or not supplying system load for a period of time during which an additional generating unit cannot be made available. This timeframe is referred to as the lead time. The PJM method assumes a constant load within the lead time, thus the load model is ignored. A pre-set acceptable risk level is used to define system risk of satisfying or not satisfying load during this period. The method works by convolving generating units to create a capacity outage probability table (COPT). SR is determined from the COPT for units within the system and included in the unit commitment process. A COPT is a list of possible capacity levels and corresponding probability of existence by the combination of all generating units owned by a facility [4]. To build the COPT, units can be combined by binomial distribution if they are identical or by other basic probability techniques

[107]. In the operating phase, the outage replacement rate (ORR) is the generating unit parameter used to evaluate the probability of having a certain capacity on outage. ORR represents the probability of a generating unit going on outage without the possibility of repair or replacement during the lead time [4]. Repair process is neglected during system operation since time to repair is usually considerably longer than the lead time. The two-state model for generating units commonly used in reliability studies [108] which define unit operating state and unit failed state as shown in Fig. 4.3 is used to determine the equation for ORR.

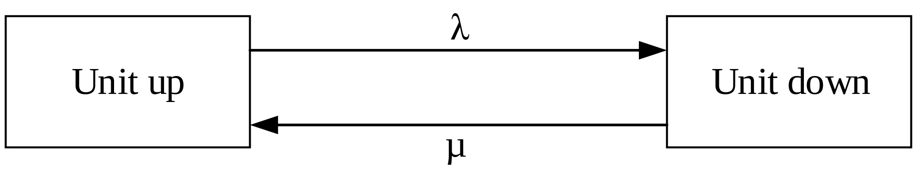

Fig. 4.3 Two-state model for a generating unit

Where λ is the failure rate which is a reciprocal of the mean time to failure, and μ is the rate of repair which is a reciprocal of mean time to repair. For a system with M units, there would be 2^M capacity states. Following the model, [107] describes the probability of finding a unit in a failed state at a time t, given that at t = 0 the unit was operating, as:

$$\Pr(\text{down}) = \frac{\lambda}{\lambda+\mu} - \frac{\lambda}{\lambda+\mu}e^{-(\lambda+\mu)t} \tag{4.1}$$

Neglecting the repair process as previously stated would mean μ = 0,

$$\Pr(\text{down}) = 1 - e^{-\lambda t} \tag{4.2}$$

Equation (4.2) represents the ORR of the unit. The ORR is a time-dependent quantity since it is affected by the lead time. Using the ORR, the cumulative probability section of the COPT can be generated with the recursive algorithm below [4] :

$$\Pr(X) = (1 - U)\Pr`(X) + (U)\Pr`(X - C) \tag{4.3}$$

$$\Pr`(X) = \begin{cases} 1, if\ X \leq 0 \\ 0, otherwise \end{cases} \tag{4.4}$$

Where C represents capacity of a unit in MW, U is the ORR value of the unit, X is a capacity outage state in MW, Pr`(X) is the cumulative probability of X MW before the unit is added, and

Pr(X) is the cumulative probability after the unit is added. The expression in Equation (4.3) evaluates the cumulative probability of X MW capacity on outage after adding a unit of C MW capacity while Equation (4.4) defines the initial stage of the expression. An example of a COPT is shown in Table 4.4 from committed generating units' data given in Table 4.3. Lead time of 2 hours is used to calculate ORR given in Table 4.3. In Table 4.4, the second column presents the capacity on outage, the third column has the capacity available, corresponding probabilities of having the outage or available states are in the fourth column while the fifth column has the cumulative probabilities as defined by Equation (4.3).

Table 4.3 Units' data

Unit no.	Capacity (MW)	λ (f/yr)	ORR
1	80	2	0.000457
2	120	3	0.000685
3	140	3	0.000685

Table 4.4 Capacity outage probability table

Capacity In (MW)	Capacity Out (MW)	Individual Probability	Cumulative Probability
340	0	0.998174	1
260	80	0.000456	0.001826
220	120	0.000684	0.00137
200	140	0.000684	0.000685
140	200	3.13E-07	1.09E-06
120	220	3.13E-07	7.82E-07
80	260	4.69E-07	4.69E-07
0	340	2.14E-10	2.14E-10

For a set acceptable risk level of 0.001, Table 4.4 shows that the committed system can supply load up to 220 MW with required SR of 120 MW. If the UC risk from the generation model is greater than the acceptable risk value, additional generating unit would be committed by merit order (operational cost increasing down the list) and the COPT recomputed until the expected load can be met at a risk value less than or equal to the set acceptable value. It is possible to reduce SR quantity by reducing the lead time for thermal units through 'banking' which was discussed in Chapter 2. Having a large SR capacity or maintaining units on hot reserve would be an economic decision for the GENCO [4].

This approach is extended to the test system in use with data given in Table 4.1, hourly offer quantity and associated SR is shown in Fig. 4.4. An increase in offer quantity would have a corresponding increase in reserve quantity to accommodate possible outage. To implement SR as part of hourly schedules, an additional constraint to be considered in optimizing the objective function as previously described is given as:

$$\mathrm{Q}^{\mathrm{h}} + \mathrm{SR}^{\mathrm{h}} = \mathrm{P}_{\mathrm{UC}}^{\mathrm{h}} \tag{4.5}$$

The equality constraint describes the total capacity of units committed at hour h as sum of offer quantity and SR. This constraint would ascertain SR is included in the unit commitment process.

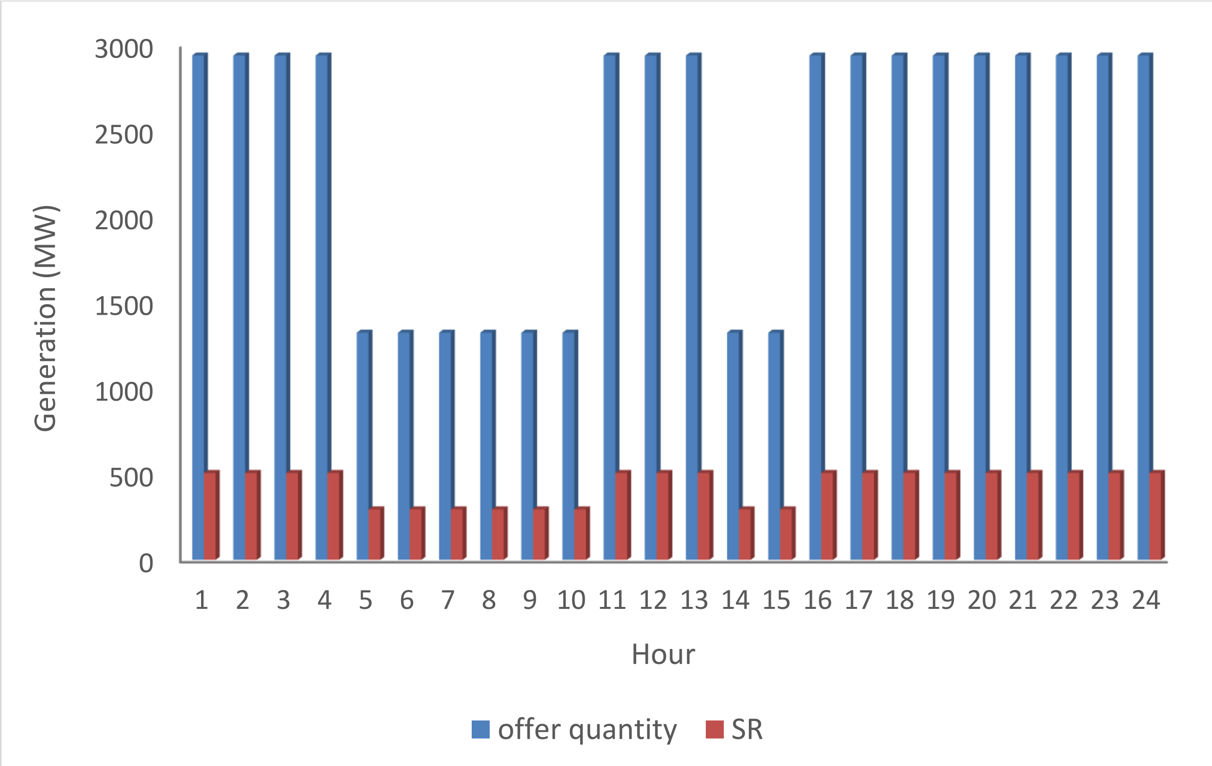

Fig. 4.4 Hourly offer quantity and reserve capacity

Inclusion of SR is to maintain GENCO's system security. It is important to note that the SR committed here is not reserve capacity for the general ISO-controlled grid, operating reserve for the entire power grid is purchased and committed through a different process described in Chapter 2. Since allocating reserve capacity would increase GENCO's operating cost, method employed to determine SR is essential. The choice of a probabilistic technique over the use of a deterministic criterion would reduce the possibility of over-forecasting the SR requirement, giving a sub-optimal solution with unnecessarily high operating cost. There would be a slight decrease in maximum offer quantity possible since with reserve requirement, all generation capacity is no longer available for sale in the electricity markets. Although this would translate to a reduction in market benefits (Fig. 4.5), reliability is a critical issue in electric power systems.

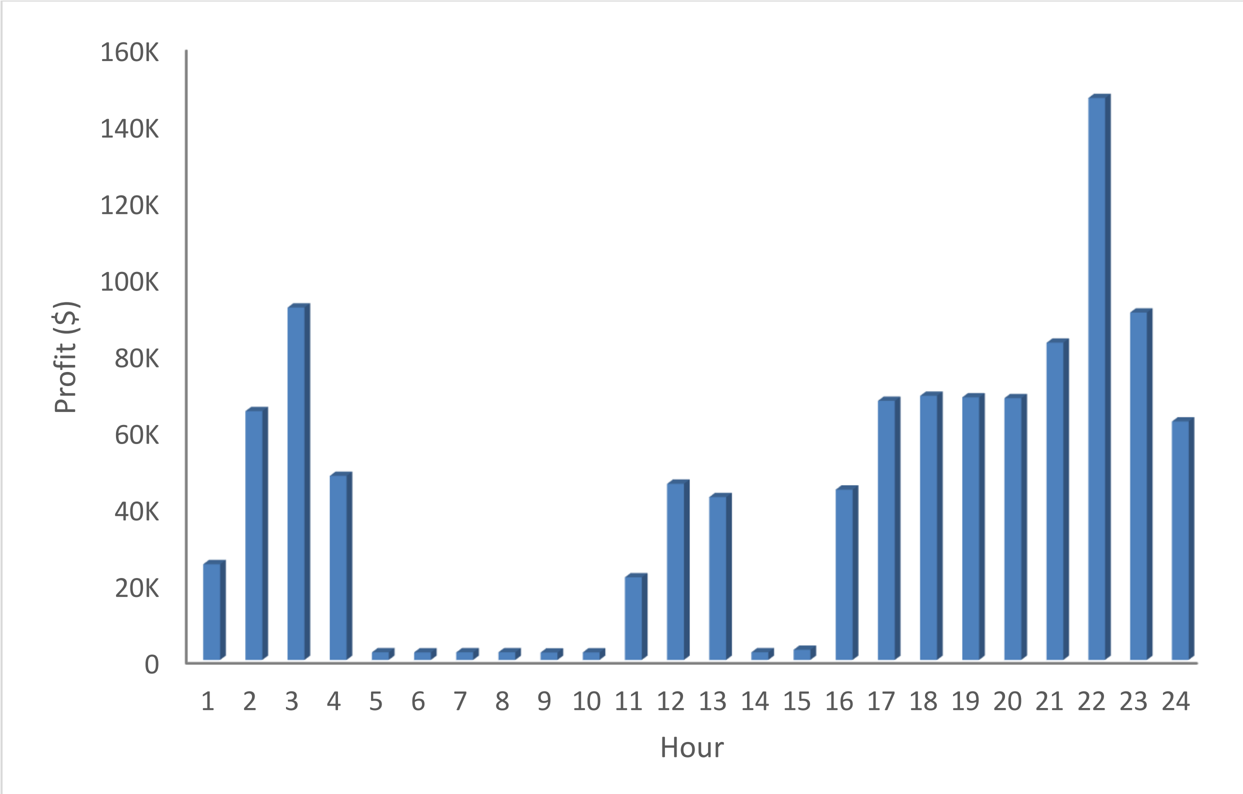

Fig. 4.5 GENCO's benefits from DAM auction process considering reserve capacity for system security

4.2.2 Effect of Load Forecast Uncertainty

As explained in Chapter 1, uncertainty in load forecast can be represented by a normal probability distribution with the distribution mean as forecast peak load and standard deviation as level of uncertainty. Accuracy desired is thus described by the number of steps (class intervals) in the distribution. In this thesis, a 5-step distribution approach is used with 3% uncertainty as shown in Fig. 1.2. This representation of the load model is seen to be adequate for the work done [9][109]. The area of each class interval is the probability of the load being in the class interval [4] and the summation of all probabilities is equal to 1. Variability in market demand presented in Fig. 4.1 is shown in Fig. 4.6, load curves representing step shift in the original demand μ under 3% uncertainty. Optimal market benefit for each load profile is calculated from the objective function while considering SR. A variation in load could relate to difference in prices. As an essential commodity electricity demand is relatively inelastic, an increase in price may translate to very little or no decrease in demand. Different prices were considered as the MCP for the 5 load profiles for each step of LFU. An aggregate hourly market benefit is shown in Fig. 4.7 obtained from the weighted sum of benefit with 5 estimated MCPs based on the load profiles.

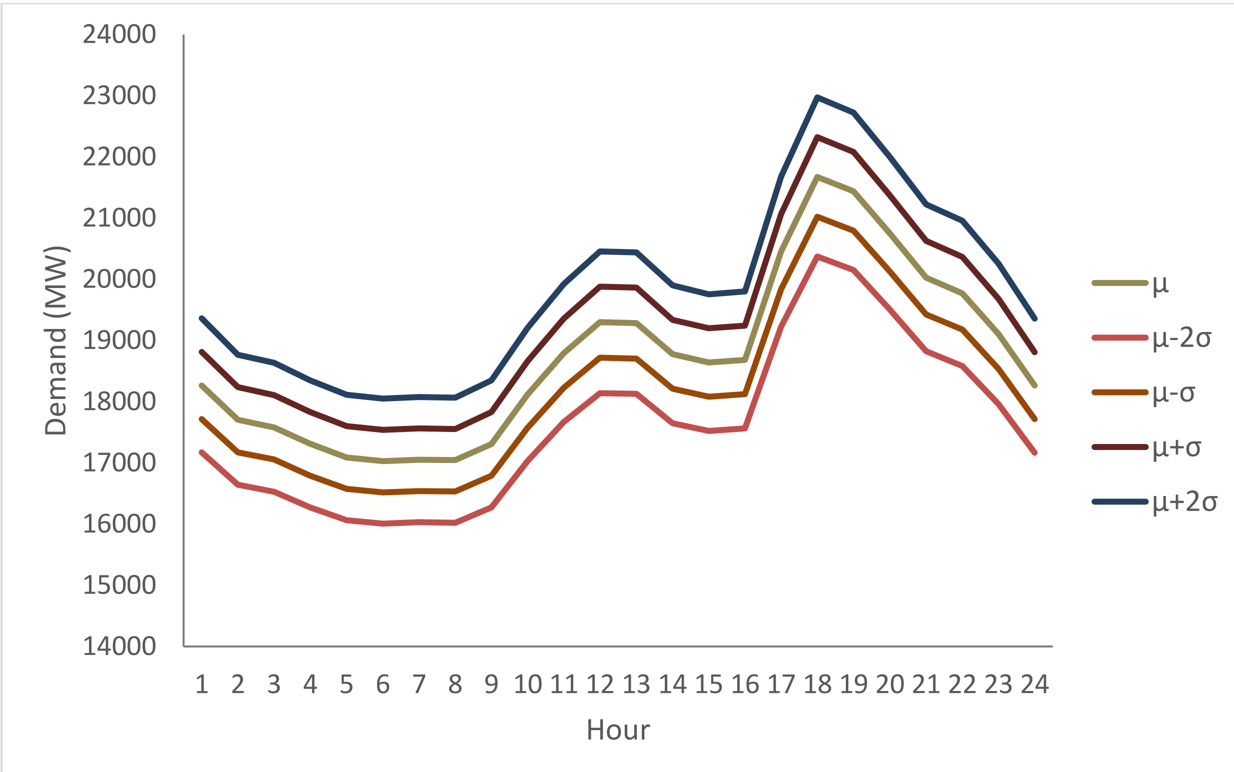

Fig. 4.6 Demand forecast for trade day considering LFU

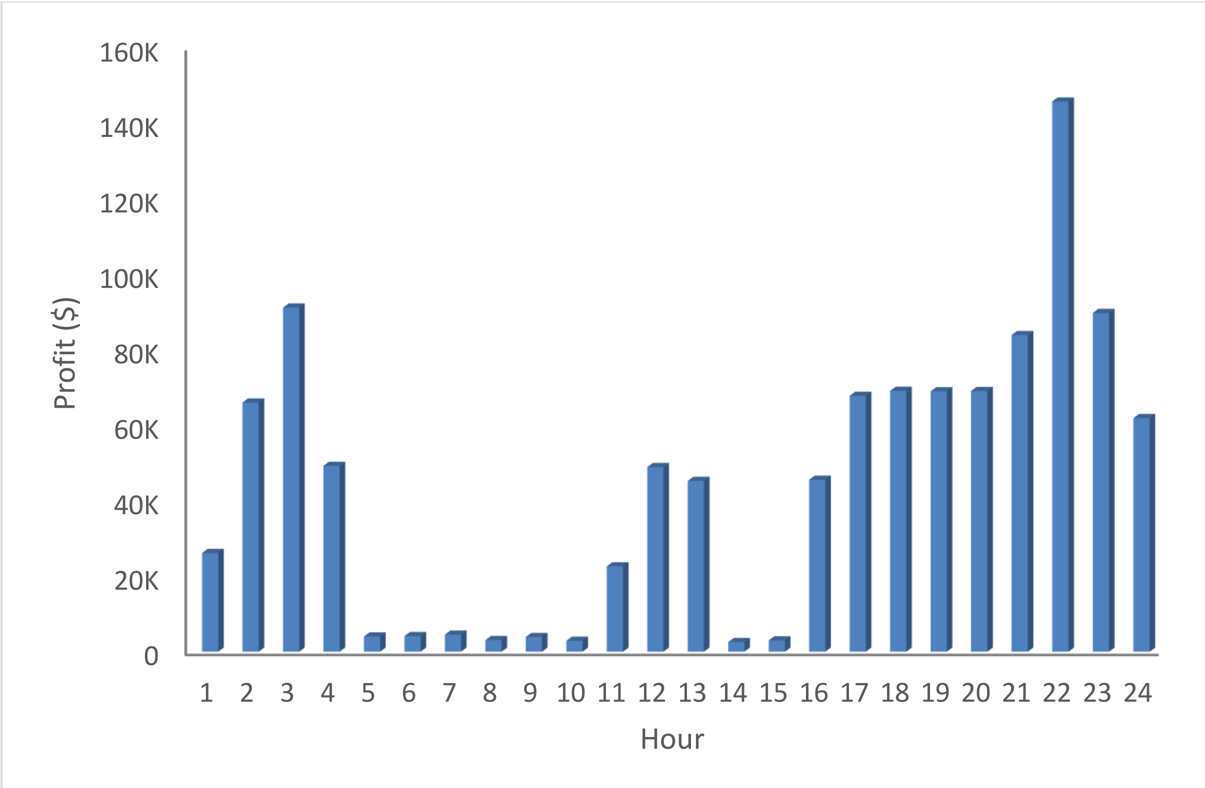

Fig. 4.7 GENCO’s aggregate benefits from DAM auction process

Comparing results from the three scenarios, Fig. 4.8 show difference in hourly market benefits. Although generating units are usually built with high reliability, ignoring the probability of an outage is an optimistic appraisal of the GENCO’s system. Contingencies such as unscheduled outages make risk assessment and provision for system security critical parts of the decision process for making offers in electricity markets. The figure also shows the output of the scenario with SR and that of aggregate from LFU to be within a close range. This is as a result of the approach being largely dependent on MCP estimates. Also, with the nature of electricity markets a slight increase in demand could make a large increase in price, depending on the mix of generating units within the system.

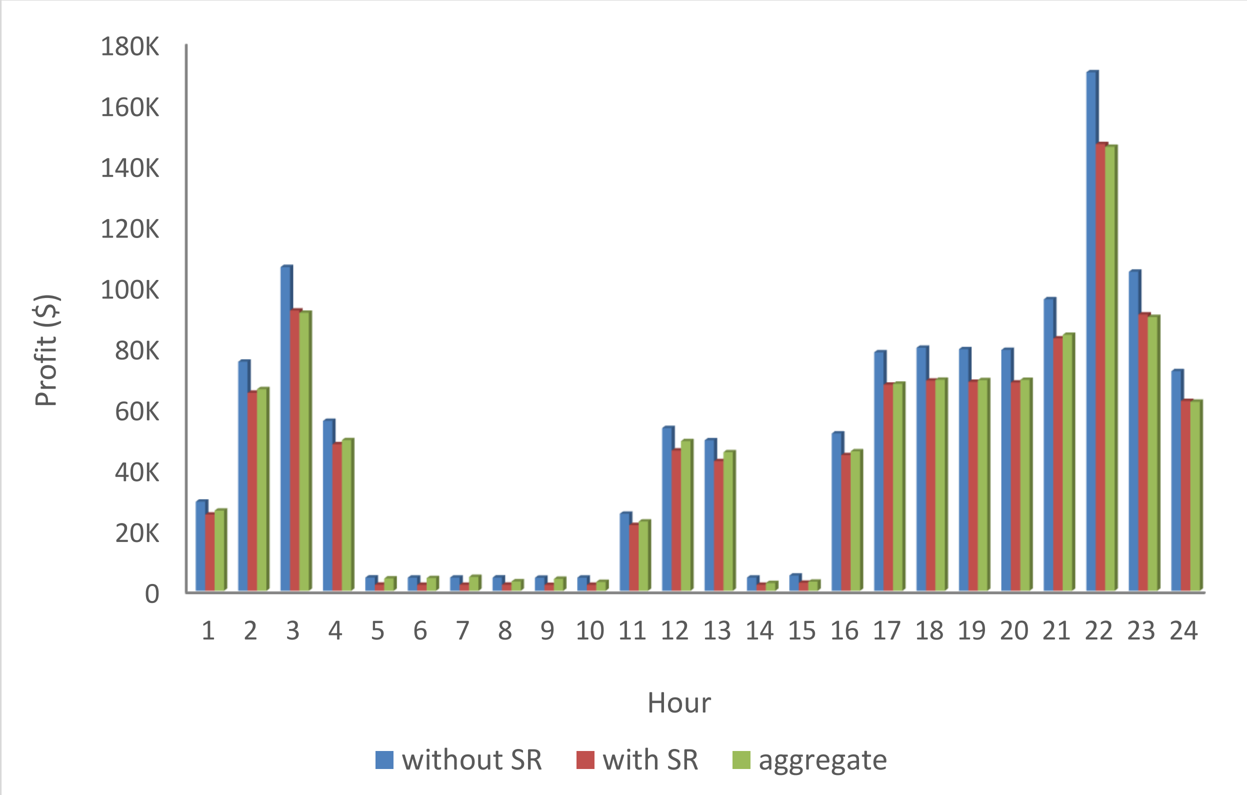

Fig. 4.8 Comparison of GENCO’s benefits from DAM auction process

4.3 Bidding in Day-ahead and Spot Markets

Transaction for power supply to satisfy real-time increase in market demand which could not have been scheduled in the DAM is done by an ISO in the SM. Energy procured from this market is at a different price; the spot market price, which can be very high when compared to the DAM prices. Increase in demand can be met either through the SM or operating reserve. The choice of which to access first usually depend on the incremental energy cost of the source, quantity increase in demand and other operational constraints. Market for operating reserve and the SM can be operated in parallel, thus separate commitment process and pricing. Since operating reserve is a form of capacity on standby, the ISO pays a fixed maintenance fee which increases overall cost of scheduling operating reserve capacity. This isn’t the case with energy procured from the SM. A SM operates within a short timeline, with energy transaction and delivery happening within minutes to a few hours. Fig. 4.9 shows hourly aggregate market benefits from the SM if the GENCO’s participation in DAM auction takes precedence over its offers in the SM. It is important to note that quantity of energy transacted in a SM is lower when compared with energy traded in DAM. The DAM auction process is where bulk of energy needed on the trade day is bought/sold. Also, since energy is only required from a SM if real-time demand is higher than forecast, it is important to estimate probability of such occurrence and amount of deviation. The results for the SM would thus be considering the +σ half of the LFU modelling.

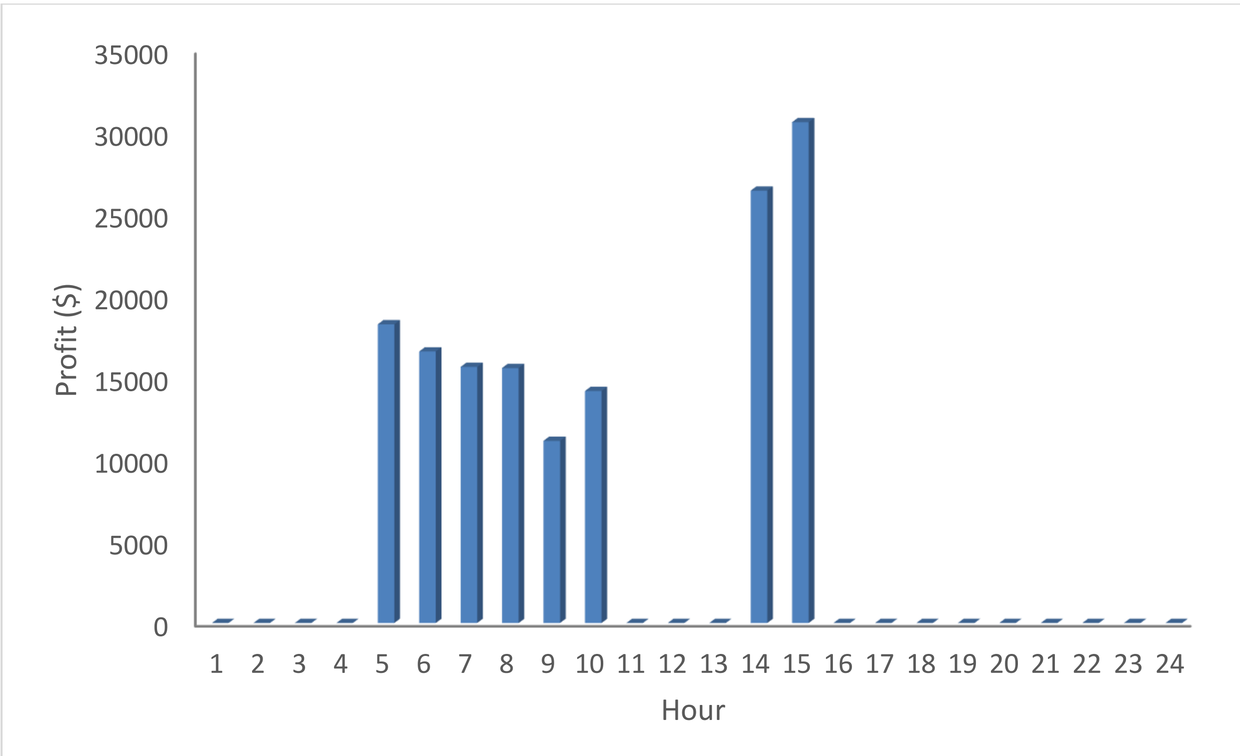

Fig. 4.9 GENCO’s aggregate benefits from SM

Hours with profit of $0 stems from zero revenue. This is as a result of the GENCO not participating in the SM at these periods as all its available capacity has been committed in the DAM auction. SR requirement is maintained and actually increases with commitment in the SM. Benefits from the DAM and the SM considering one step deviation from forecast is presented in Fig. 4.10. Hours where commitment in the DAM is low show more returns from the SM. At this level, the GENCO is operating at maximum capacity with full commitment at every hour.

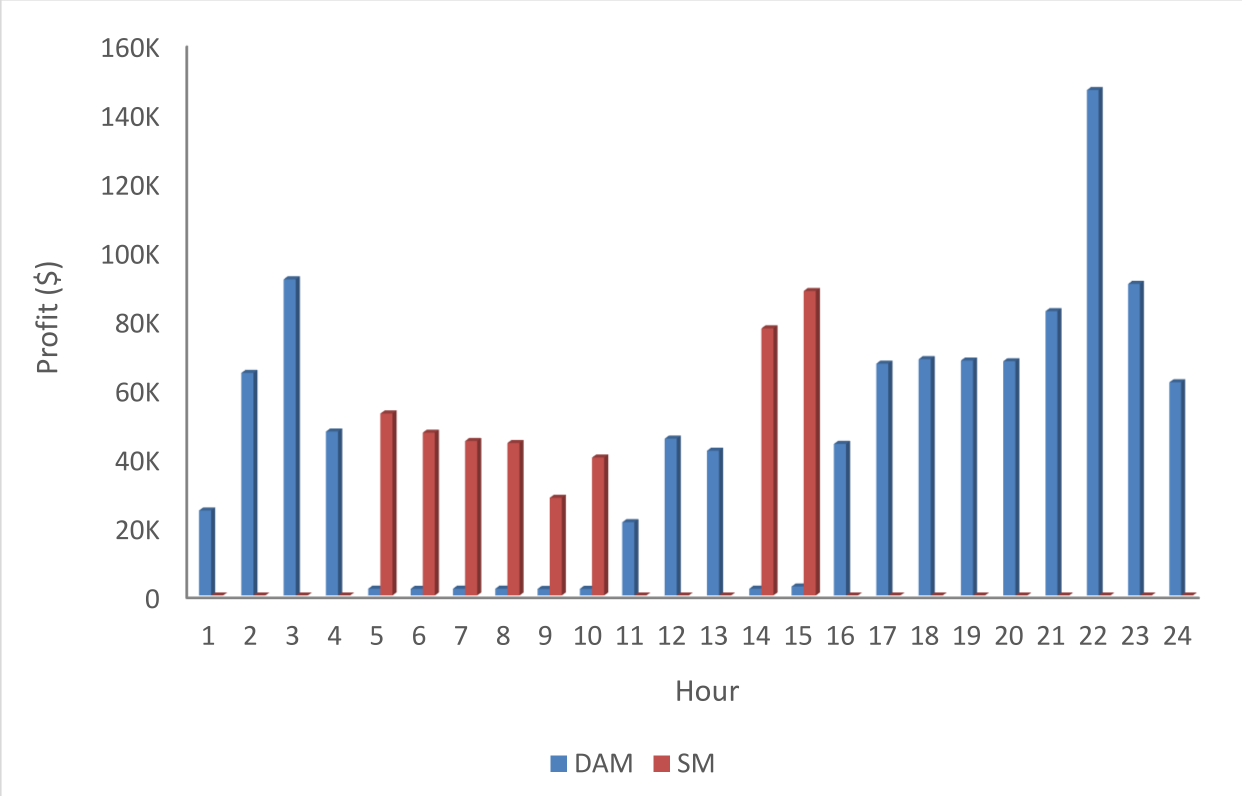

Fig. 4.10 GENCO's benefits for a step deviation

4.3.1 Effect of Allocating Percentages

The scenario in the previous section commits capacity left from bidding in the DAM in the SM. However, due to efficient forecasting methods, difference in real-time demand and forecast is usually not very large. Thus, the volume of energy traded in the SM is low as compared to the DAM. With high prices as a feature of the SM, an allocation of the GENCO's generation capacity to both the DAM and the SM auction is considered. Since the SM participation is only feasible when demand is more than forecast, capacity for the SM is included for $+\sigma$ steps deviation only. To consider both markets concurrently at every hour, 95% of generation is committed in the DAM auction at periods where commitment was previously maximum and 5% in the SM for an uncertainty of $\mu+\sigma$ in demand. For a deviation of $\mu+2\sigma$, 90% and 10% of generation are committed in the DAM and the SM respectively. Fig. 4.11 shows hourly aggregate market benefits from the SM. The GENCO has a commitment for the SM at every hour unlike what can be observed in Fig. 4.9. Although the GENCO's benefits is lower with percentage allocation considered, committing very large quantity of generation in the SM is rather optimistic and can result in a loss for the GENCO.

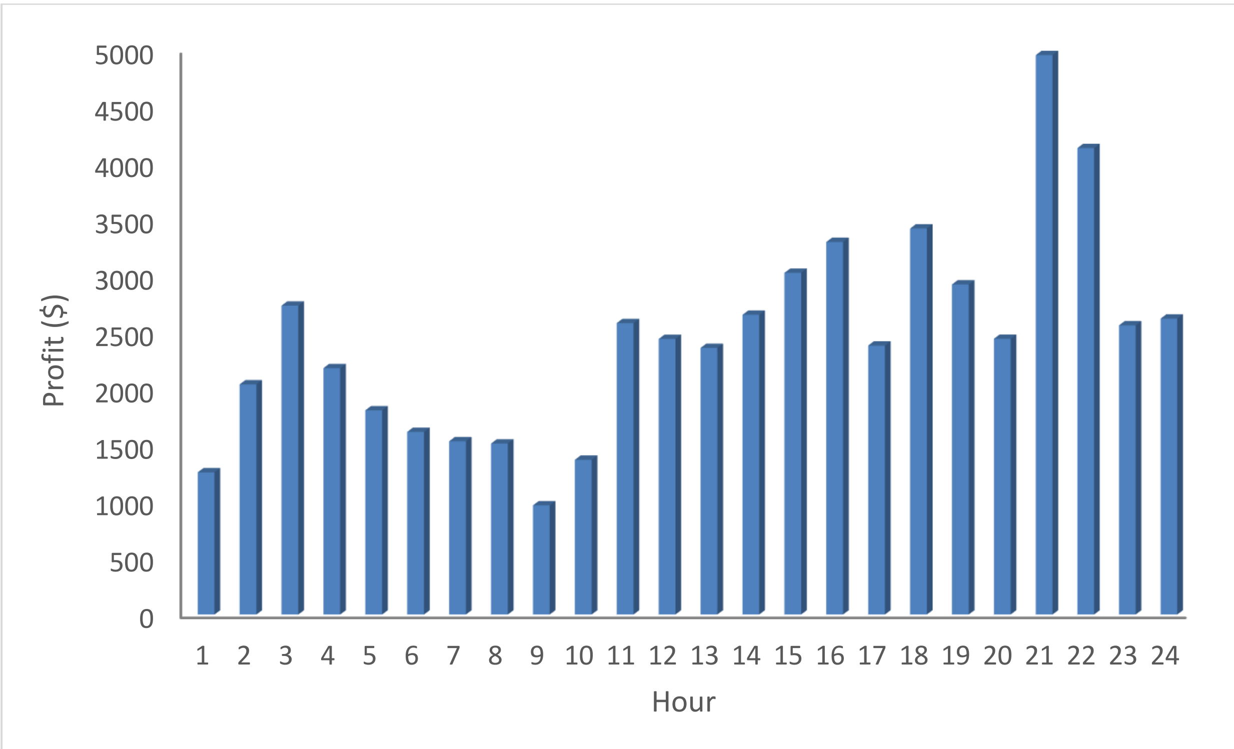

Fig. 4.11 GENCO's aggregate benefits from SM with percentage allocation

GENCO's benefits from both the DAM and the SM auctions at $\mu+\sigma$ and $\mu+2\sigma$ are shown below. The day profit from the DAM auction process decreases when compared with previous scenarios since generation quantity committed is lesser. However overall day benefits from both markets is an improvement on this due to high energy prices feature of the SM.

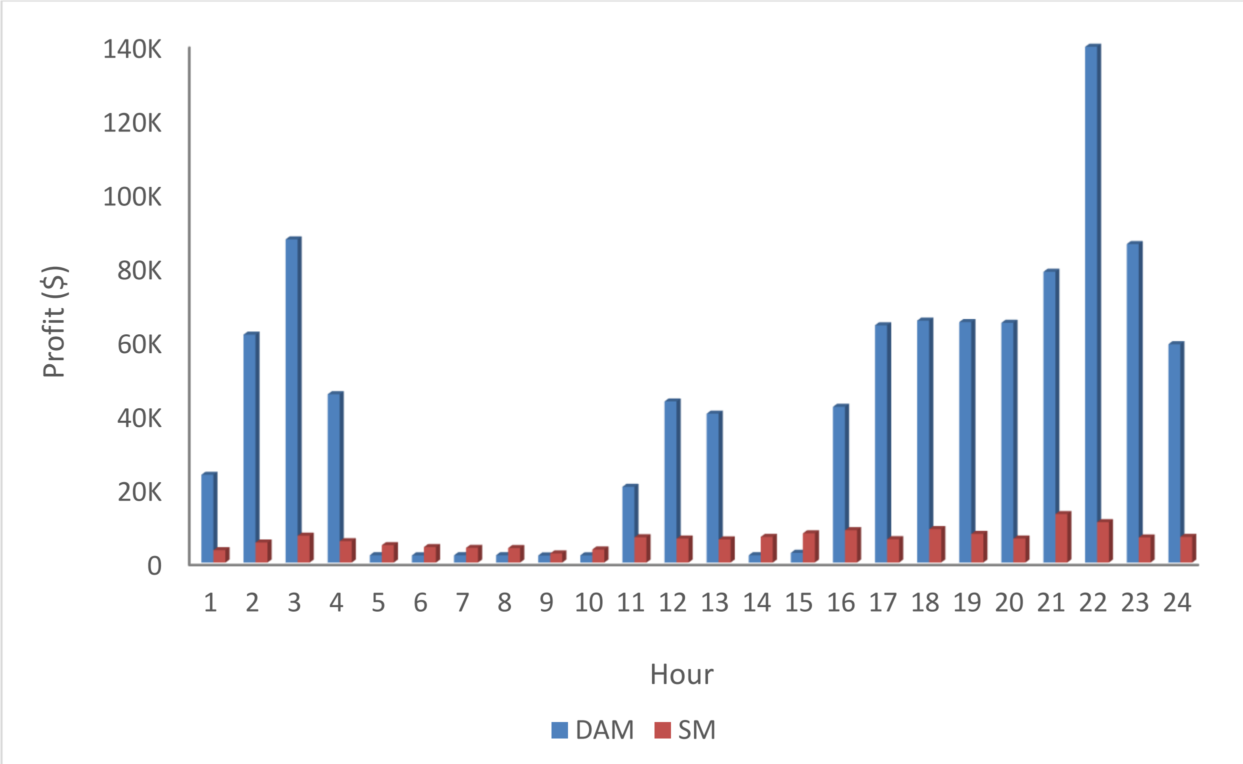

Fig. 4.12 GENCO's benefits for a step deviation with 95/5 ratio

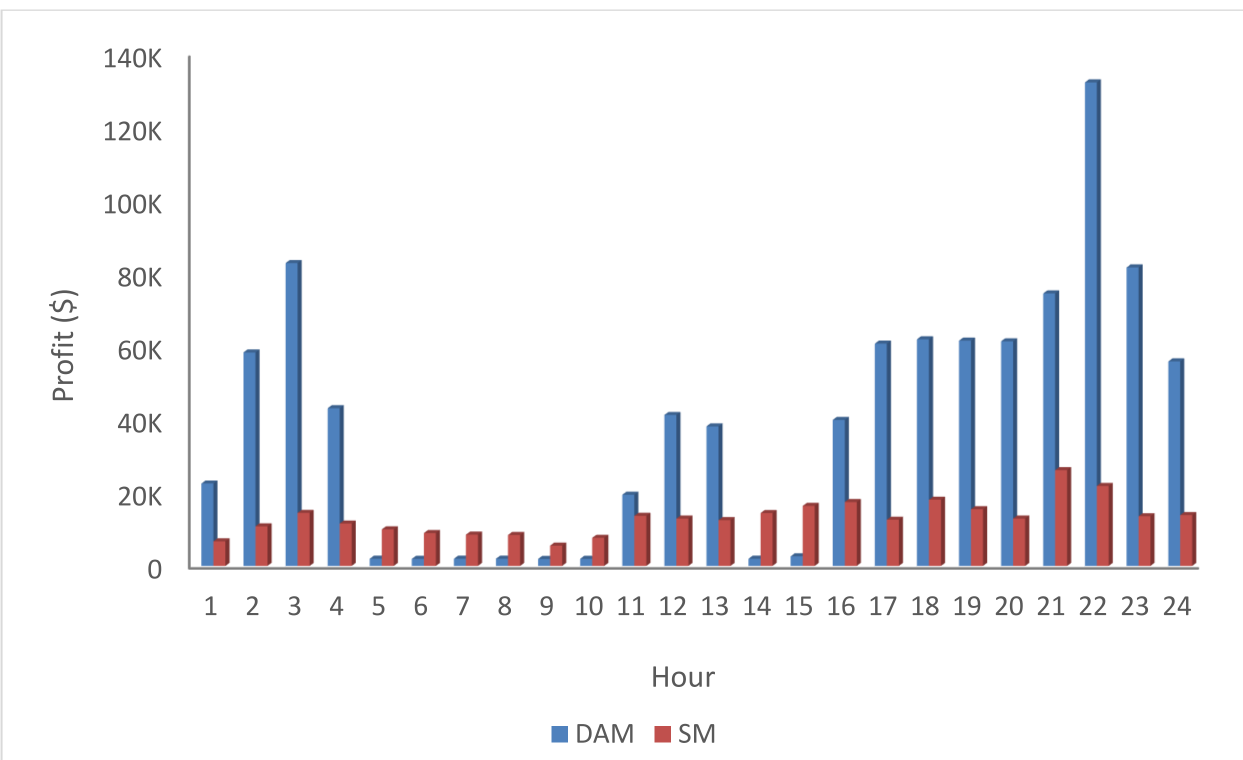

Fig. 4.13 GENCO's benefits for 2-step deviation with 90/10 ratio

Estimated benefits at the end of the trade day from participation in both day-ahead and spot electricity markets are presented in Fig. 4.14. SR for GENCO's system security is kept as a requirement for all periods and in both markets with capacity on reserve increasing with increase in load level. The initial case of aggregate day profit represents GENCO trading only in DAM considering LFU (Fig. 4.7). LFU is thus considered from two aspects in this research work. First is variability in market demand for DAM auction process with GENCO making commitments only in the DAM. The LFU is considered in the decision process for supply offers in the DAM. Second is participation in SM as a result of uncertainty in demand. In this situation the commitment for DAM remains as decided but decision process includes SM at +σ uncertainty.

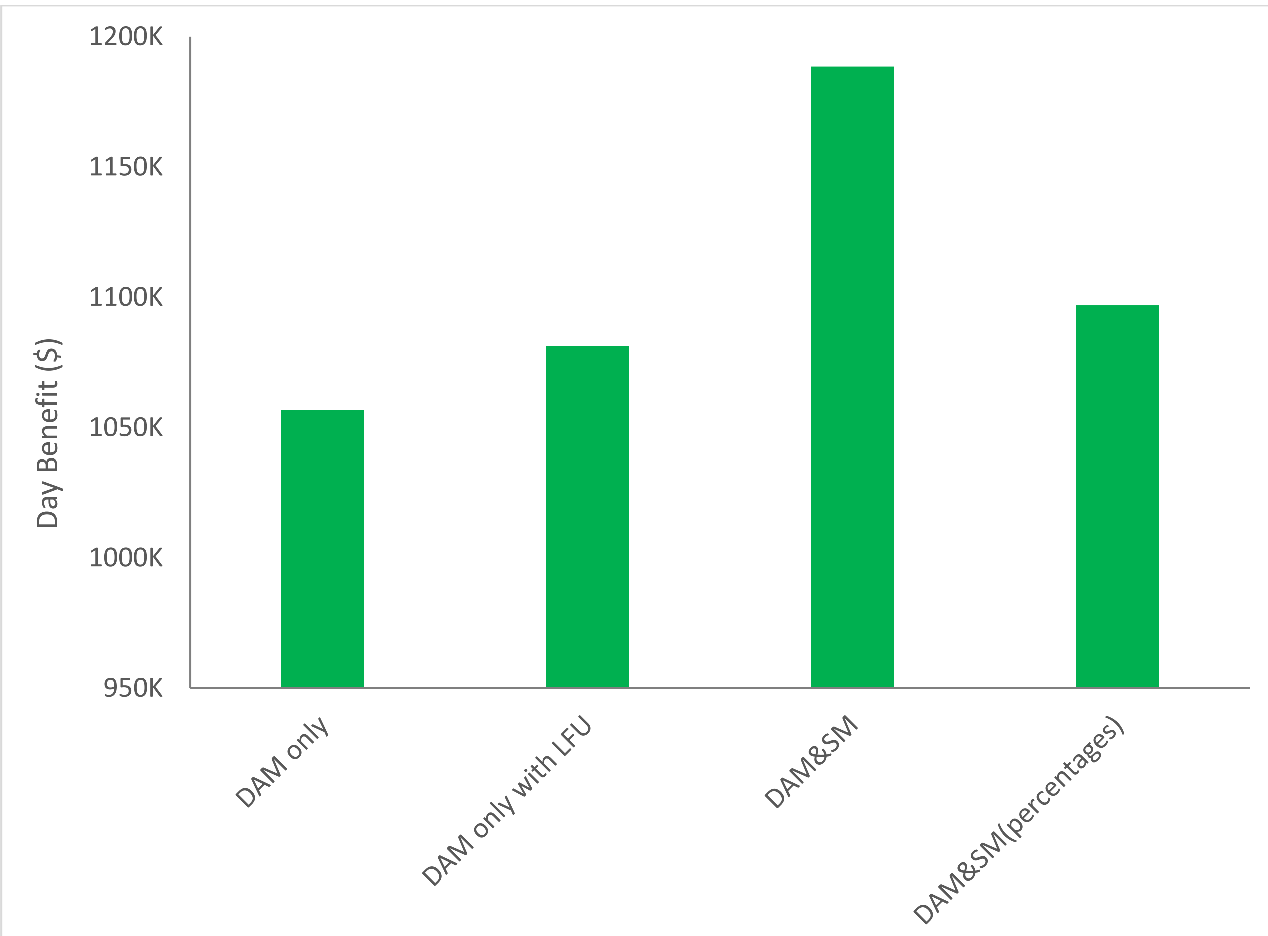

Fig. 4.14 GENCO's estimated benefits at the end of trade day

4.4 Summary

Together the results discussed in this Chapter provide important insights into strategies that can be employed by GENCOs for maximum benefits from their participation in electricity market. The proposed approach estimates the short-term hourly MCP based on past market observations and behaviour of competing GENCOs. Estimated MCPs are inputs to the optimization problem of determining profit-maximizing supply quantity by a GENCO. An economic load dispatch algorithm is run to ensure generating units are running at minimum operating cost. This is especially important when considering technical and operational constraints. A test system of a GENCO with twelve thermal generating units is used to simulate the proposed approach and assess the offers and corresponding benefit from market for each hour of the trade day. Effects of having reserve capacity for GENCO's system security has been evaluated. SR for each supply level has been determined through a probabilistic method. Capacity on reserve needs to be carefully assessed as it increases the system operating cost. Another important factor considered was load forecast uncertainty. Uncertainty in market demand forecast for the trade day would affect the general operation of the energy markets, the MCP, and the market clearing volume, which would extend to GENCO's supply offers. These factors in different scenarios have been analyzed for the day-ahead and spot energy markets.

CHAPTER 5

CONCLUSIONS

5.1 Conclusions

This research work set out to examine strategies that could be used by GENCOs to maximize profits from their involvement in electricity markets. Electric power industry in many regions operate as deregulated entities, moving from the traditional vertical integrated structure. Main reason for deregulation in this sector is to satisfy the increasing demand for electricity in an efficient manner and also lower electricity price. Power generating plants are owned by GENCOs who manage these facilities and compete to supply electric power in the various electricity markets. Competition, a product of deregulation, drives innovation which is a necessity in a dynamic industry. An ISO manages the operation of the electricity markets, accepting offers to supply from GENCOs and demand bids from consumers. Supply curve is built by ranking GENCOs' offers in order of increasing price while the demand curve is obtained in a similar fashion with bids ranked in a decreasing order of price. The MCP for the interval under consideration is the price at the point of equilibrium between demand and supply and is determined by the ISO. GENCOs with bids below and at this price are paid the MCP and are scheduled to supply for the interval. A sealed-bid auction process is usually followed, thus, participating GENCOs have no information on rivals' supply offer curve. This makes the task of determining offer quantity and corresponding price an important one for a GENCO in order to maximize its market returns and also minimize the risk of not being scheduled to supply. A factor considered in this research work is a GENCO's ability to concurrently participate in more than one electricity market.

Analyses have been performed on strategic bidding by a GENCO in electricity markets using optimization models. Many of the methods are based on estimating rivals' bidding behaviour by determining their bid coefficients. These techniques rely on having access to sufficient data on bidding history in the market. This may be difficult to obtain in practice. The approach proposed in this thesis takes incomplete market information on auction process into consideration for a short-term analysis of a GENCO's activities in electricity markets. The period considered is ≤ 14 days prior to a trade day. The approach is divided into three steps: estimating hourly MCP, determining the profit-maximizing offer quantity with the MCP as an input, and running a DP process for economic dispatch of generating units to minimize operating cost. There are several studies on electricity market demand and price forecasting. An ISO as the market operator continuously makes short-term to long-term market demand forecasts, making necessary adjustments as consumption day draws closer. This information is usually made available to market participants. Market participants such as GENCOs can also make demand and price predictions with historical data readily available from the market. The DSHW method is applied in this research work for short-term MCP prediction. The method is based on the principle of exponential smoothing for forecasting time series with dual seasonal pattern. Electricity market demand and price show seasonal variations. The problem of determining the hourly offer quantity was defined as an optimization problem with the objective function as profit maximization subject to generating units' limits constraint. The fuel cost is the cost associated with power generation considered and it is defined as a quadratic function. This problem was solved for each generating unit using a priority list to obtain the profit-maximizing supply offer. The GSSO method was applied to solving the optimization problem. The method adequately represents the one-variable optimization problem, searching for solution within a boundary defined by constraints. Dispatching scheduled generating units to supply power and satisfy other operational constraints in a manner that the running cost (fuel cost) is minimum is an important step in determining a GENCO's market benefits. The economic dispatch of GENCO's generating units is an optimization problem solved by DP process in this research work. The exhaustive search feature of the DP procedure is an advantage in its application to the economic dispatch problem.

A GENCO's outlook for a typical trade day was simulated using a test system as described in Chapter 4. With a demand forecast from the ISO, previously described steps were followed to make supply offers in the DAM as one of the electricity markets. The DAM is a forward market for bulk energy needed the following day. Although the DAM timeline differs in regions, the market usually closes a day prior to the trade day. Results show estimated profit-maximizing supply quantity to be dependent on predicted hourly market prices. GENCO's system security and market demand forecast uncertainty are two factors whose effects on bidding process and market operation are considered in the evaluation of GENCO's benefits from the electricity markets. Since there are rules guiding operation of electricity markets, GENCOs are obligated to supply at periods they are scheduled. Having some part of the GENCO's capacity on reserve to withstand contingencies such as loss of generation which would affect the GENCO's ability to deliver scheduled supply was examined. SR which is generating capacity synchronized to the system is the type of operating reserve considered for unit commitment risk. Many utilities use some deterministic criteria to assess SR requirements. While they offer security and are easy to apply, using these fixed/deterministic techniques may give a sub-optimal solution. Since having reserve capacity would affect the system running cost, a proper estimation of the SR is important in determining maximum market benefits. A probabilistic technique was used in this research work to determine hourly SR quantity. This technique gives a better representation of the system parameters and solves limitations of the deterministic methods such as overscheduling of reserve capacity. With a set risk level, SR quantity is estimated from a COPT for units within the system. The SR requirement adds a constraint to the hourly unit commitment and economic dispatch process done by the GENCO. In the optimization problem of minimizing the system running cost, total capacity of units committed in an interval should equal sum of previously evaluated supply quantity and SR requirement for such load (generation quantity) at the interval. The SR requirement changes with change in load level. It increases with increase in load and decreases as estimated load reduces. Although the SR requirement generally increases running cost and reduces the generation quantity available to the GENCO for bidding in the electricity markets thereby reducing benefits, it is necessary for a reliable operation of the GENCO's system. The market demand forecast uncertainty also referred to as load forecast uncertainty relates to the variability associated with making predictions for market demand of electricity. Factoring in this uncertainty is pertinent to maximizing market benefits as it affects unit scheduling, dispatch and thus system reliability. The LFU was described by a 5-step normal distribution with the mean as the forecast load and standard deviation as level of uncertainty. With 3% uncertainty, offer quantity and price were evaluated for load profiles representing each step deviation. Variation in load could lead to change in MCP. This would affect profit-maximizing offer quantity calculated. Thus, there could either be an increase or decrease in hourly estimated benefits depending on the direction of the uncertainty ($+\sigma$ or $-\sigma$). These scenarios were examined for the DAM only at first.

After looking into the effects of LFU on the DAM and market demand in general, GENCO's participation in a second type of energy market called the spot market was introduced. The SM is a real-time market to maintain continuous balance between energy demand and supply on the trade day. The SM is for responding to shortage in supply when real-time demand is more than previously scheduled supply done with demand forecast. It can also help with contingencies such as congestion and unscheduled loss of generation within the ISO's grid. The market timeline is usually very short and electricity price is much higher than what can be gotten in the DAM. Since energy from SM is needed when real-time demand is more than forecast, the SM is considered for positive step deviations in the normal distribution (+σ). At these instances, the variability is an increase in market demand. As bulk of the energy needed has been settled in the DAM auction process, the quantity traded in the SM is small. Parallel participation of GENCOS in both the DAM and SM was examined. To take good advantage of the high energy price feature of the SM, an instance of apportioning supply ratios for each market was considered. This was done bearing in mind the level of uncertainty in the market. Although GENCO's benefits with this process is better than when operating in the DAM only, it is lesser than having all of the remaining generating capacity after bidding in the DAM and keeping SR requirement offered in the SM. Following the latter would be a rather overly optimistic appraisal of the SM with the level of uncertainty defined and total energy volume traded in the market.

The findings of this research work add to the rapidly expanding field of economic operation of independent power producers in deregulated electric power industry. Notwithstanding the governing market rules such as having bid price caps and operating mode limitations usually put in place by an ISO (market operator) and which vary with regions, the approach proposed in this study would prove useful in expanding the understanding of market participants and other stakeholders in analyzing the operation of GENCOs in electricity markets. The results address the salient question of what a single GENCO's supply offer price and quantity could be in each of the daily energy markets at each period or market interval (usually hourly) for it to maximize benefits from its operation at the end of a business day. GENCOs may base their offer price on market price predictions, adjusting offer quantity through time as necessary. The DAM and SM are the two markets covered in this research work since they are the markets for the bulk trade of electricity.

5.2 Suggestions for Future Work

With the growing popularity of hybrid approaches to forecasting, this study could be repeated using one of such methods for the MCP prediction. Also worthy of note is the effect of price spikes. To improve forecast accuracy, spike data points are exempted before applying a forecasting model which lessen their effect on the approximation of the model parameters. However, since electricity prices can be volatile, an analysis of price spikes may be a significant step for GENCOs to maintain efficient operation in the competitive electricity markets. The issue of ensuring GENCO's system security by keeping a reserve is an intriguing one which could be usefully explored in further research. A cost/benefit analysis can be done to assess the option of having some of the thermal generating units on hot reserve ('banking') to reduce lead time as oppose to maintaining what could be a large SR for each market interval. These would be fruitful areas for further work.

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