ELECTRICITY MARKET BIDDING DYNAMICS CONTROLLED BY HYBRID GENETIC PARTICLE SWARM TUNED SLIDING MODE CONTROLLER

THESIS

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BONAFIDE CERTIFICATE

Certified that this thesis titled **"ELECTRICITY MARKET BIDDING DYNAMICS CONTROLLED BY HYBRID GENETIC PARTICLE SWARM TUNED SLIDING MODE CONTROLLER",** is the bonafide work of Ms. INDHU P.NAIR, who carried out the research under my supervision. Certified that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion of this or any other candidate. Certified further that all the suggestions/corrections, from the adjudicators, have been incorporated.

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When the world says, "Give up,"

Hope whispers, "Try it one more time." - Author Unknown

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LIST OF ACRONYMS

ANN	: Artificial Neural Network
AR	: Autoregressive
ARIMA	: Autoregressive Integrated Moving Average
ARMA	: Autoregressive Moving Average
BMNS	: Buyer Motivated Negotiation Strategy
BSMC	: Back stepping Sliding Mode Control
CHP	: Combined heat and power station
DAM	: Day Ahead Market
DER	: Distributed Energy Resources
DR	: Demand Response
DSM	: Demand Side Management
EE	: Energy Efficient
EPRI	: Electric Power Research Institute
GA	: Genetic Algorithm
GARCH	: Generalized Autoregressive Conditional Heteroskedasticity
GPSO	: Genetic Particle Swarm Optimization
HOSMC	: Higher Order Sliding Mode Control
IEX	: Indian Energy Exchange
ISO	: Independent System Operator
MA	: Moving Average
MAE	: Mean Absolute Error
MAPE	: Mean Absolute Percentage Error
MAPS	: Market Assessment and Portfolio Strategies
MCP	: Market Clearing Price
MIMO	: Multi Input Multi Output
PAB	: Pay As Bid
PCA	: Principal Component Analysis
PCM	: Profit Ceiling Model
PI	: Proportional Integral
PID	: Proportional Integral Derivative

PPF	: Parametric Pure Feedback
PSD	: Power Spectral Density
PSF	: Parametric Strict Feedback
PSO	: Particle Swarm Optimization
PXIL	: Power Exchange of India Ltd.
RMSE	: Root Mean Square Error
RPI-X	: Retail Price Index
ROR	: Rate of Return
SCOPF	: Security Constrained Optimal Power Flow
SMC	: Sliding Mode Control
SOSMC	: Second Order Sliding Mode Control
VPP	: Virtual Power Players

Chapter 1
Introduction

1.1.Background:

Basically, the electric power industry involves the generation, transmission, and distribution of electricity to the end use customers. Across the world, the power industry is treated as a natural monopoly for the most part of the 20^{th} century. However, in recent years it has undergone a significant restructuring process or deregulation process. In fact, since the 1980s, the trend in many countries has been to reshape the traditional regulated power industry in a more open way, with the aim of encouraging competition and thus increasing its efficiency. The evolution of power system industry is as shown in fig.1.1.

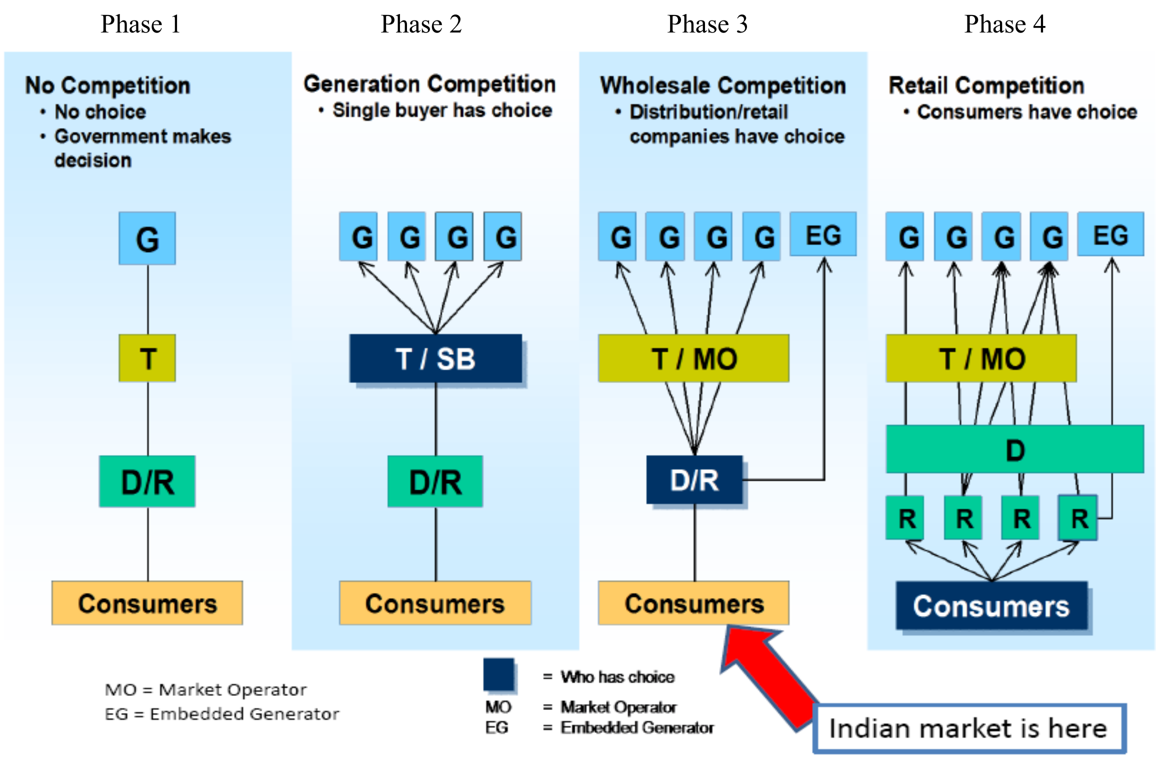

Fig.1.1.Evolution of Power Industry(Courtesy: Internet source)

In phase1, the power industry is acted as a vertically integrated monopoly from generation to retail and customers have no choice. Often, the government supervises or regulates the cost structure and rate of return during phase1. In the initial stage of unbundling or during phase 2, the majority of the power industries are opened up by the generation side and hence single buyer has a choice. During phase 3 of deregulation process, the generation and transmission areas are opened up to provide a more competitive electricity market. The majority of the electricity markets in developing countries are now at this stage. Here, the distribution /retail companies have the choice to select a particular producer. In the latest development of deregulation or during phase 4, competition is introduced in the distribution area. During this phase, the end use customers have the choice to select a particular retailer.

The core of deregulation process is the creation of mechanisms for power suppliers, and sometimes for large consumers, to openly trade electricity. Or in other words, bidding is the major mechanism introduced in the power industry due to the deregulation process. Ideally, the market structure and management mechanisms (rules) in an electricity market are sufficiently well designed. The competition among participants is sufficiently vigorous to direct the operation of the market towards maximizing social welfare. It implies that in a well-designed electricity market no loopholes can be exploited and no scope is left for gaming that disrupts operations and/or distorts prices. However, the emergent electricity market structure is more akin to oligopoly than the perfect market competition. This is due to special features of the electricity supply industry such as**,** a limited number of producers, large investment size (barrier to entry), transmission constraints which isolate consumers from the effective reach of many generators, and transmission losses which discourage consumers from purchasing power from distant suppliers. All these make it practicable only for a few generating companies to serve a given geographic region. At this time, each supplier can maximize profit through strategic bidding.

The deregulation of electricity markets around the world has raised many new challenges for all stakeholders. The modeling of the electricity market is a basic yet critical problem for all stakeholders and provides the foundation for many decision-making problems within electricity markets.

1.2.Relevance of the topic in the present scenario:

Privatization and competition in power industry are introduced with an aim to reduce the electricity price and to ensure reliable power supply. Generally, the power industry reforms help the industry to become consumer oriented or more efficient. However, with the introduction of competition, the power industry is transformed to a structure built on the electricity market concept. Hence, the bidding process becomes the heart of power industry which determines the electricity price to be paid by the end use customers. Any chaos in the bidding dynamics may result in high volatility in electricity prices and may affect the stability of the demand- supply relation. The above situation may end up in the collapse of the power industry. Hence, the control of bidding dynamics is very essential for the stability of the market and to reduce the electricity price to be paid by the end use customers. Moreover, there are very few studies related to the electricity market bidding process in developing countries.

1.3.Motivation for the Research work:

First motivation: After the restructuring of the power industry, most of the research works in this area are related to two major concerns. These are economic concerns such as the trading process, supply- demand balancing etc. and power system concerns such congestion management, power system reliability etc. In fact, the economists analyze the system based on the past data without considering the dynamics of the system. Since the electricity price or Market clearing price (MCP) is the outcome of bidding dynamic process, the modeling of trading/bidding process is required to solve even the economic concerns. In a pure financial system with perfect competition, the MCP or equilibrium point is obtained as the intersection of supply and demand curve. In fact, the system like an electricity market, it is not purely of having economic concerns alone but has control engineer’s aspects also. The equilibrium point in demand supply relation can be obtained in a control system point of view [1].

Second motivation: Chaotic systems belong to a subclass of deterministic dynamical systems and are generally complicated and unpredictable in nature. After the detection of chaotic behavior in economics by Grandmont and Malgrange[2], many researchers tried to link the role of chaos with the inherent randomness in macroeconomics models[3,4]. This uncertainty can make precise financial forecasting very limited. This reduces the effectiveness of government sector to control an economic system. In the U.S., subprime mortgage illustrated the ineffectiveness of government policies to counteract the critical economic behavior which resulted in global economic crisis. This may be because of the chaotic nature of the financial system. Motivated by this theoretical and practical background, modeling and control of nonlinear chaotic finance systems have been an active topic of study for the last few years and a novel financial hyper chaotic system was developed in 2012[5], suited for the highly nonlinear complex global economy. In this context, many methods and techniques have been developed to control the chaotic financial system. They are mainly passive control [3], back stepping control and sliding mode control [6]. Among the different techniques mentioned above, the sliding mode control (SMC) can deal with the uncertainties/chaotic nature of the financial system. In SMC, the major issues are related to the design of sliding mode controller specifically the design of sliding surface. Once an appropriate sliding mode surface is designed, the controller can restrain the effect of chaotic nature of the system and has stronger robustness on the external force disturbances. However, the design of the coefficients of the sliding surface for the present chaotic finance system mainly depends on the designer's experience. Hence, so far there is no systematic design procedure developed for the design of sliding surface coefficients.

Motivated by these two streams of research, the aim of the research work is chosen as to develop a sliding mode controller to control the electricity market bidding process in a developing country.

1.4.Objectives of the research work:

- To develop a block diagram approach of electricity market dynamics in control system perspective.
- To investigate the existence or nonexistence of chaotic behavior of electricity market clearing price in a developing country.
- To develop a Hybrid Genetic Particle Swarm optimized (GPSO) sliding mode controller to stabilize the chaos present in the bidding dynamics.
- To analyze the scope of Profit Ceiling Model to regulate electricity market in developing country.
- To develop a negotiation strategy to motivate the buyer.

1.5.Organization of the work/thesis:

Phase I (Chapter 3):

Motivated by these research works and the practical evolution of power industry, a block diagram (BD) approach of bidding dynamics is developed. In the BD approach, which is suitable for the electricity market in developing countries, the electric load value (demand) is chosen as a known value since the load forecasting research is almost at its saturated stage with less than 1% forecasted error values For the price forecasting a chaotic model is developed and the forecasted price is given as inputs to other stages. In the power exchange, there is long term market as well as a day ahead market. In the long term market, generally the Bilateral Contracts are characterized by the establishment of bilateral financial or physical relations between generation entities, on one side, and eligible customers or retailing agents on the other side. These contracts involve several aspects as the price and energy to be supplied and consumed over a specified period of time and usually, these contracts are the outcomes of a negotiation process. Based on the demand side management concept, a buyer motivated negotiation strategy (BMNS) is developed. In BMNS, the seller and buyer agents after negotiation agree upon a fixed price for a fixed volume. At the same time, a regulation model applicable for developing countries is proposed to ensure the social welfare. The PCM proposes a range of values for market clearing price as input to the independent system operator (ISO). ISO is the one who selects the bid from the bids submitted by the generators. In a perfectly competitive environment generators get the maximum pay off if they bid for their marginal cost. However, this is not applicable in oligopoly market where the majority of market share lies in few suppliers. So generators have to adjust their bids suitably. In the proposed scheme, the controller specifically the sliding mode controller adjusts the bidding variables of the generators to get max pay off.

Phase II (Chapter 4):

The electricity prices in developing countries exhibit extreme volatility due to its non-storable nature, supply constraints at peak hours, transmission line congestion at peak hours and seasonal and diurnal variations. As an example, the day-ahead market price of Indian Energy Exchange (IEX) is collected and the detailed analysis of market clearing price (MCP) of IEX is done. This analysis clearly indicates the chaotic nature of data. It is because of this chaotic behaviour, the phase space of the time series data is reconstructed using Taken's theorem. With the concept of add weighted one rank multi-step model, the MCP of IEX is modeled as a chaotic model from this reconstructed phase space. Furthermore, the developed chaotic model is verified for forecasting MCP and the simulation results demonstrate that the chaotic model developed outperforms the Autoregressive integrated moving average (ARIMA) model and Generalized autoregressive conditional heteroskedasticity (GARCH) model (existing models from literature) in terms of forecasting performances.

Phase III (Chapter 5):

Market participants, specifically retailers and end-user customers, should be able to enter into bilateral contracts to protect themselves from volatility, notably market clearing price volatility. Hence there should be provisions for negotiation framework allowing the participants to prepare offers and counter-offers and to reach superior agreements. Therefore, the participants should be able to exhibit strategic behavior, notably submitting offers that promote demand response. In this context, a negotiation strategy applicable for developing countries namely Buyer motivated negotiation strategy (BMNS) is proposed. BMNS consists of a volume management strategy for end use customers and a price management strategy for producers. The simulation results, obtained with the proposed strategy, prove the intelligent speculation that the behavior of market participants is as expected in managing energy prices and volumes. The results also confirm that the simulation tool currently being developed can help the decision process of the negotiating parties during bilateral contracting of electricity in competitive energy markets.

Phase IV (Chapter 6):

In all the developed countries, either the Rate of Return (ROR) model (generally used in countries like USA) or Retail Price Index (RPI-X) model (generally used in countries like UK) has been employed for regulating the electricity prices. Since these two models are the models generally employed in regulating electricity markets, the inherent draw backs of these models in regulating electricity market in developing countries are identified. The existing Profit Ceiling model(in financial markets), eliminates the identified drawbacks when used in Electricity markets in developing countries. The Profit Ceiling Model (PCM) emphasizes on the quantitative relation between price level and uplift. To identify the quantitative relation between price level and uplift, the regulatory authority is expected to forecast and promulgate the uplift for the next year to implement the proposed PCM effectively. The uplift forecast can be treated as an optimization problem where the objective function is to maximize the allowed uplift for the next year. In this work, the optimization problem is solved using Hybrid Genetic particle Swarm Tuned Optimization approach and is found to be very effective in terms of computational complexity and optimization. The PCM incorporates the incentive mechanisms for new and aged power plants. The major characteristics of PCM are the regulatory control on the price level, profit regulation, uplift evaluation and incentives for investors.

Phase V (Chapter 7):

Generally, for any system, if the system is chaotic in nature, then the response would also be chaotic. In the present case, using chaotic theory, the electricity price (response) is proved to be chaotic in nature. This confirms the chaotic nature of the system. Or in other words, the electricity prices which show chaotic nature are the outcome of a system (electricity market) with chaotic dynamics. The bidding dynamics existing for an oligopoly electricity market, with adaptive and rational dynamics, is modeled in state space form and the dynamics are found to be highly chaotic in nature. The chaos present in the bidding dynamics can be stabilized at the equilibrium point with the help of a sliding mode controller. In the proposed sliding mode controller, back stepping techniques and sliding mode control are combined to improve the reaching phase as well as steady state characteristics of the controller. Moreover, sliding surface parameters are optimized using a hybrid Genetic Particle Swarm Optimization (GPSO) algorithm. The efficacy of GPSO algorithm in tuning the parameters of the sliding mode controller is clearly perceptible in the numerical simulation results. The comparative study with other techniques shows the effectiveness of the hybrid Genetic Particle Swarm tuned sliding mode controller in improving the reaching phase characteristics as well as the settling time required for the chaotic bidding dynamics to reach a stable equilibrium point.

Phase VI (Chapter 8):

Lastly, in this work, the bidding process is modified with the concept of prosumers, i.e., the same market player can act as producer and customer. In the market policy developed, the prosumers participate in the open market, buying and selling active and reactive power to the grid. The prosumers are charged for their active and reactive power consumption at the rate of MCP. The modified bidding dynamics show the chaotic nature. Hence a hybrid genetic particle swarm tuned sliding mode controller is developed to stabilize the chaos present in the modified bidding dynamics.

Conclusions, major contributions and inferences are described in chapter 9. The scope of future works is also discussed in the chapter.

1.6.Major contributions:

- Design of a chaotic model for predicting the chaotic electricity price series.
- Development of Buyer motivated negotiation strategy based on demand response management concept.

- Formulation of a hybrid GPSO algorithm for optimization.
- State space modeling of bidding dynamics with prosumer as one stake holder.
- Design of a hybrid GPSO sliding mode controller to stabilize the chaos present in the electricity market bidding dynamics in developing countries.

Chapter 2
Literature Review

2.1.Introduction

A power producer in the vertically integrated monopoly market operates in such a way to equalize the demand and supply by ensuring adequate security with minimum cost [7]. Since 1980s, the electricity markets have been slowly growing toward deregulated competitive energy markets. To encourage healthy competition in deregulated environment and thereby improve the efficacy, the market players are allowed to participate in gaming and resulted in the emergence of several new technologies/ developments [8, 9]. The market players in the electricity market are expected to make proper decisions with insufficient information such as the electric load uncertainties, the behaviour of rivalries' and power system contingencies.

The deregulated electricity market differs from other financial markets due to the characteristics such as the peculiarities of electricity as a commodity, the physical constraints of the transmission network, long construction period and large capital investments for the power plants, and few power suppliers [10]. In an oligopoly market, only a few producers serve a particular geographic area and hence these few producers can affect the market clearing price by using their market power. Therefore, the producers or generation companies may increase their profit by optimizing their bidding strategy [11]. At the same time, the market players face associated risks and market uncertainties during the optimization process [12].

The chapter is organized as follows. Section 2.2 gives a general introduction to the bidding problem and thereafter, the related literature is categorized according to their modeling algorithms. In Section 2.3, demand side management is treated as a separate section, since the concept is used for developing a novel negotiation strategy. In section 2.4., electrical price forecasting techniques developed so far are reviewed in detail. In section 2.5, the control strategy adopted to stabilize the chaos specifically the sliding mode control and application of soft computing technologies in the sliding mode control algorithm are discussed. Conclusive remarks, as well as some possible directions for future research, are finally presented in Section 2.6.

2.2.Literature Review on Bidding Dynamics of Electricity Market:

In a perfect electricity market, any power supplier is a price taker, not a price maker. According to microeconomic theory, the generator agent or power supplier will get maximum profit when bids at its marginal cost. Whenever a supplier bids higher than its marginal cost, the aim is to exploit market imperfections to increase profits, this bidding behavior is termed as strategic bidding. Therefore, if a power supplier can increase its profit without lowering its cost, the supplier is said to have market power. The electricity markets in developing countries are not a perfectly competitive market and hence by exercising the market power, the generator can increase their profits. Hence bidding problem can be treated as an optimization problem to maximize the profit of generator's using strategic bidding.

The performance efficiency of any financial market is calculated by the economic concept called social welfare [13]. Social welfare is a permutation of the cost of a commodity and the need of the commodity to society as calculated by society's willingness to pay for it. Generally, a perfectly competitive market maximizes social welfare. Real markets always function at a level lower than maximum social welfare. The difference between the social welfare of a perfectly competitive market and a real market is considered as the measure of the inefficiency of the real market. Hence bidding problem can be revisited as maximization of generator's profit without compromising much on social welfare.

The bidding problem in electricity markets is associated with electricity market pool concept. The power suppliers submit bids to the independent system operator (ISO) and bids should comprise of the price, quantity and time frame. Depending on the demands of large consumers and distributors, the ISO determines the winning bid and the market clearing price. While this procedure is done in the day ahead market (DAM), there are some bilateral contracts between the seller and buyer for the long term. These bilateral contracts entertain the negotiation process also. In developing countries, the restructuring introduces competition mainly on the generation side and the distribution and transmission are in still in monopoly, the bidding problem deals with power suppliers.

Generally, there are three different ways to develop optimal bidding strategies of Generators/ power suppliers. First one depends on the forecast of MCP during the next time period. The second one is based on the estimation of bidding behavior of other market players/rivalries. The third one is basically the game theory. In spite of these three methods, some works are based on empirical analysis and market simulation approach.

The first method, the simplest one, is to offer a biding price less than the forecasted MCP. However, this method requires a thorough understanding of the market as a whole to get an accurate estimation of MCP. In addition to this, in an oligopoly market, the bidding strategy of each power supplier affects the MCP. Hence this method is seldom applicable to generate the optimal bidding strategy of power suppliers, especially in developing countries.

The majority of the works to develop optimal bidding strategy are based on the estimation of bidding behavior of the opponents. The methods normally adopted for behavior estimation are probability analysis, fuzzy sets and so on.

The third method is based on some techniques adopted from game theory. Many techniques are developed under this category and basically, they are divided into two groups. The first group is based on matrix game where the bidding strategies are presented as discrete states such as high, low and medium. However, in real electricity market the strategies cannot be discrete and therefore this method is not an appropriate one. The second group uses the strategies of oligopoly games such as supply function, Stackelberg model, and Cournot Model. While analyzing these models, it is evident that these models are more suitable for evaluating the market power rather than for developing the optimal bidding strategies. Some works are reported to develop the bidding strategies based on the principle of these games, as the equilibrium state of the game corresponds to the optimal bidding price. However, this is not true for the case of real oligopoly market due to the numerous simplifications and assumptions made in the course of application of these models.

Normally, the economic mechanism used during the formation of all electricity markets is an auction. So, bidding is an issue connected with an auction. Development of optimal bidding strategy should be based on the auction rules, protocols and generally the market model. The auction methods can be classified into static and dynamic. If the bidders are submitting sealed bids, the procedure is termed as static and if they can observe the bids of opponents, then it is dynamic in nature. In dynamic auctions, the bidders can revise the bids sequentially. An auction procedure is termed as a double side when both the players (sellers and buyers) are submitting the bids. Even though, most of the operating electricity markets in the world are now employing the sealed bid auction with uniform market price, very few markets are based on Pay As Bid (PAB) pricing. In PAB price mechanism, the supplier is paid at its bidding price for the committed quantity rather than the market clearing price. Hence, in PAB market the bidding strategy is very important and more complex in nature than that of uniform price markets. Generally, in PAB markets the producers forecast the uncertain MCP and bid for a price less than that of the marginal cost. The PAB market is the latest trend in electricity markets and the simulation studies reveal that market clearing price, as well as the price volatility, may be reduced in PAB markets [14, 15].

Another factor influencing bidding strategy is bidding protocol. Bidding protocol defines whether the bid should contain several price components or a single price component. Generally, power suppliers bid independent prices for each block and market clearing mechanism will determine the MCP and schedule for the block concerned. This method is fundamentally decentralized, means the market operator does not make unit commitment decisions and hence does not guarantee feasibility. Therefore, whenever there is a technical constraint or congestion the method requires another short term balancing mechanism. The single-part bid is employed in several electricity markets such as California, Australia and Norway/Sweden.

Some of the publications addressed to develop optimal bidding strategies are as follows:

A simple suboptimal bidding strategy is proposed for an electricity market with 2 buyers [16]. Here, the cost function of the players is modeled with probability density function. The major drawback of this method is that it cannot be extended to a general case with multiple numbers of players. A dynamic model of strategic bidding procedure with three players is proposed in [17] and the modeling is based on the heuristic approach which relies on historical data. Again, this model is not applicable to a general market structure with more than three players.

A linear supply function model is proposed to analyze the bidding behaviour and the different ways to exercise the market power. The proposed approach is used to develop optimal bidding strategy where the bidding behaviors are expressed as discrete probability distribution function [18]. The bidding problem is treated as an optimization problem specifically as a multiple stage probabilistic decision-making problem and Markov Decision process is employed to solve the same [19]. In [20], since the treatment of rivalries behaviour as a probabilistic function is not realistic, a heuristic method specifically fuzzy inference system is proposed. An artificial intelligent technique such as genetic algorithm and finite state automata are utilized for developing evolutionary and adaptive bidding strategies [21, 22].

A few works have been carried out with multiple period auctions. Multiple period auctions are proposed as a two level optimization procedure [23], with a centralized economic dispatch and self-unit commitment problem as two levels. This work assumed that the complete information about the competitors is known and hence it is not reasonable. A Lagrangian relaxation based method is offered for daily bidding and self-scheduling decision [24]. Here, the bids are in terms of quadratic functions of power supply levels, and the parameters in rivals' bids are assumed to be known. A systematic approach is developed for bidding strategy optimization and verified using Californian day ahead market [25].

An iterative bidding strategy is recommended, where the market players can revise their bids by applying certain rules and specifications [26]. The computational complexity is more and hence the method is not possible for a practical environment. An asynchronous iterative bidding mechanism is suggested in [27]. This method employs a feedback mechanism by which the suppliers can modify their bids and a radial basis neural network is used as a feedback mechanism.

In developed countries such as California, New Zealand, and Spain, the electricity markets are now permitting demand side bidding. Using demand side bidding, large consumers can react to the variations in MCP and can employ strategies to increase their benefits. In this approach, maximization of social welfare is the primary motive to determine the market clearing price.

Very little work has been carried out in the area of demand side bidding and the possible impacts of the demand side bidding on electricity market are analyzed in [28]. The demand side bidding is treated as a two level optimization problem with the objective function as maximization of social welfare [29]. The biding function of generators and consumers are treated as linear functions and the bidding strategy problem of both are addressed simultaneously in [30].

2.3.Literature Review on Demand Side Management:

The environmental considerations, as well as economic limitations, make the generation based approach, unsustainable and non-optimal in long term aspects. Conversely, now a day's demand side management (DSM) is proved to be a better replacement to generation based approach in power industry. The concept of DSM was first initiated by the Electric Power Research Institute (EPRI) in 1980. This concept involves some activities to be performed by the end use customers to change the energy consumption pattern or to reshape the load profile for maximizing their benefits; induce some delay in investments and to enhance the reliability aspects [31]. The latest developments in the restructured power industry, the DSM can be categorized into two.

(i) Demand response (DR) actions: changing the energy consumption pattern of end use customers from their normal state according to the variation of energy market prices, or in response to the incentives proposed for lowering the usage at peak price periods or when the reliability of the power system network is at risk.

(ii) Energy efficient (EE) appliances: by incorporating regulatory aspects induce the consumers to buy energy efficient equipment/appliances even though the initial investment is high. [32].

Some aspects of energy efficient concept could increase the energy market competition and hence may decrease the market power of the dominant supplier. This reduction in market power improves the market performance as such and thus reduces the market clearing price into a realistic price [33].

By incorporating the incentive mechanism, the flexibility in energy consumption pattern helps the market operator to schedule the physical transactions more effectively [34]. For example, if the customer's demand response program results in the reduction of market price in the National Electricity Market Singapore (NEMS), an incentive is offered [35]. The received incentive will be proportional to the saving of customer in terms of MCP. In California market, if the demand response bid is lower than the forecasted electricity price, then proxy demand response is paid based on its effect on market performance [36, 37]. In New Zealand electricity market, instead of giving incentives, the payment to be made by the user is reduced according to the demand response actions [38].

The demand response programs include the reshaping of loads of end use customers in response to the retailer's price. The customer will shift the loads from expensive periods to the periods where the electricity is cheaper. This, in turn, increases the retailer profit and this phenomenon is demonstrated by a simulation study in [39]. However, the real world implementation of this program is less, but now attracting popularization due to the introduction of electric vehicles and other storage devices.

With the increased intervention of renewable sources, another demand response action may more widespread in future. Instead of the load shaping of end use customer load profile, the market operator can reshape the load profile for efficient scheduling. For example, generally wind energy penetration is more at night and hence the market operator can shift some load valley to have more efficient market performance.

2.4.Literature Review on Electricity Price Forecasting:

In the current deregulated power industry scenario, the forecasting of electricity demand and price have emerged as one of the hot research topics in power engineering fraternity [40]. A lot of research works are carried out in this area and many methods and techniques are developed for electricity load and price forecasting. Among this, the load forecasting field has reached its saturation stage in such a way that load forecasting algorithms with mean absolute percentage error (MAPE) below 3% are available [41,42]. On the other hand, price-forecasting techniques are still in their early stages of development. While analyzing the electricity prices from real markets, it is evident that price curve exhibits more volatility than load curve [43]. The price curve is normally affected by seasonality and calendar effects and it exhibits characteristic such as high frequency, nonconstant mean and variance. The reasons for these peculiar characteristics of electricity price are due to the (i) non-storable nature of electrical energy, (ii) the physical requirement of power system network to establish constant balance between demand and supply, (iii) inelastic nature of demand over short time period, and (iv) Oligopoly nature of market. In spite of these characteristics, In addition to these characteristics, the stability of market is always affected by the uncertainties in either generation or consumer side [44]. Even precise load forecasts cannot assure profits and the market risk faced by market players are large due to the extreme volatility of electricity prices. Hence, price-forecasting methods are highly essential for all market participants for their existence under new deregulated environment.

The different models for electricity price forecasting are:

a) *Game theory models*

The first category is based on game theory. In an oligopoly market, the suppliers bid higher than their marginal cost and according to the game theory, the price is fixed as result of a particular game strategy. Several types of game strategy and the determination of their equilibrium point are available in literature like Nash equilibrium, Cournot model, Bertrand model, and supply function equilibrium model. A detailed discussion on game theory models can be found in [45].

b) Simulation models

In the second category of price-forecasting techniques, a simulation of market model is built and the price is forecasted using the simulation algorithm by employing different physical conditions. Price forecasting by simulation methods mimics the actual transfer of electricity with system parameters and constraints. It intends to solve a security constrained optimal power flow (SCOPF) with the entire system range. The major simulation models developed are market assessment and portfolio strategies (MAPS) algorithm developed by GE Power Systems Energy Consulting [46] and the UPLAN software developed by LCG Consulting [47].

c) Time series models

The third category is known as Time series analysis models and is generally focused on the past behaviour of dependent variables [48]. In some models, exogenous variables are also included within a time series framework. Based on time series, there are further three types of models.

i. Parsimonious stochastic models:

The financial market as well as energy market adapt many stochastic models and widely applied in practice. These models are autoregressive (AR), moving average (MA), autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), and generalized autoregressive conditional heteroskedastic (GARCH)[43].

ii. Regression or causal models

The basis of Regression type forecasting model is the hypothetical relationship between a dependent variable (electricity price) and a number of independent variables that are known or can be estimated [49]. The price can be formulated as a function of some exogenous variables. The exogenous variables may be identified by the correlation analysis of these variables with the price (dependent) variable.

d) Artificial intelligence (AI) models

In this type, mapping of the input–output relationship without exploring the underlying process is carried out. The characteristic of AI models to learn complex and nonlinear relationships which are difficult for conventional models is used for mapping the input-output relation. The AI models can be further classified into (i) artificial neural network (ANN) based models and (ii) data-mining models.

i. ANN based models.

By extracting the patterns from the historical data, ANN modified its structure to mimic the market structure in future [50]. The available NN models are: (i) multilayer feed forward NN (FFNN), (ii) radial basis function network (RBF), (iii) support vector machine (SVM), (iv) self-organizing map (SOM), (v) committee machine of NNs, and (vi) recurrent neural network (RNN).

ii. Data-mining models.

In recent days, data-mining techniques like Bayesian categorization method, closest k-neighbourhood categorization, and reasoning based categorization, genetic algorithm (GA) based categorization, have gained popularity for data interpretation and inference collection. The data mining property of these models is utilized for predicting the electricity prices [51].

Electricity market prices are assumed to be stochastic in nature and a regression model was developed in [52]. In [53], prices are assumed to be piecewise stationary and forecasting is done at multiple regimes with a constant price load relationship in each regime. Using wavelet transform the price series is decomposed and for forecasting purpose, the behaviour is predicted in wavelet domain and transformed into price domain. The concept of regression polynomial is applied for forecasting in [54].

ARIMA method is applied to predict the electricity price and load series in [55, 56]. The performance of AR and ARMA models in predicting the uni-variate time series are compared in [57]. ARIMA model with the seasonal process is presented in [58, 59]. A GARCH model, the modified ARMA model with GARCH error components, is proposed in [60]. The concept of time segmentation, framing the time series into 24 distinct time series is proposed in [61]. In [57], it is also demonstrated that the time segmentation strategy improved the forecasting performance.

The reconstruction of phase space based on chaos theory is presented and RNN is applied to predict the load and price series in [62]. ANFIS, Adaptive Network based Fuzzy Inference System is proposed in [63]. There the output is determined as a linear function of input variables and its membership functions. The inputs are obtained from a price simulation concept and are used to train the neural network in [64].A linear regression model for long term forecasting and NN model for short term forecasting were developed in [65].Spot market prices are predicted by applying the auto correlated chaotic model in [66]. Based on the input-output hidden Markov model, the electricity market dynamics is represented by two states; hidden state and visible state. The proposed model switches between these two states and NN for implementing hidden state sub network, the regression model for output or visible state sub network [67].

The major issue for the success of all forecasting technique depends on the selection of input component. Many methods and techniques are developed for this, such as Principal component analysis (PCA), correlation analysis, genetic algorithm (GA), sensitivity analysis, spectrum analysis techniques. Sensitivity analysis to show the effect of input variable is performed in [68, 69].Feature selection correlation analysis is performed in [63]. Even though, all these methods are developed, there is still a deficit for an accurate analytical method to select a minimum number of effective input features.

Some of the major works in short term electricity price forecasting is tabulated in table 2.1.

Author	**Nature of data taken**	**Electricity Market**	**Models used**	**Forecasting Performance Measures**
Contreras et al.	Day Ahead Market Clearing Prices	Spain(OMEL) and the Californian Pool(CalPx)	ARIMA	Daily Mean Error (around 8%)
Cuaresma et al.	Hourly spot electricity prices	Leipzig Power Exchange(LPX), Germany	A battery of Uni Variate time series Models (AR(I), AR(I) with varying intercept, ARMA with time varying intercept, Crossed ARMA with time varying intercept, ARMA with jumps and Unobserved Component model)	Root Mean Square Error (4%), Mean Absolute Error (2.568%)
Weron and Misiorek	Hourly spot electricity prices	Californian Power Exchange (CalPx)	• ARMA • ARMAX • ARMAX with Spike Preprocessed • AR with GARCH residuals • Regime Switching model	MAE, MAPE, MDE, MWE, DRMSE, WRMSE Comparing the values of these performances indices, ARMAX with Spike Preprocessed is found to be the best candidate.
Weron and Misiorek	Hourly spot electricity prices and hourly temperatures	Californian Power Market and Nordpool Power Market	• AR model • Semi Parametric Models • Spike Preprocessed model • Regime Switching model	MWAE, MWE, MAPE Comparing the values of these performance indices, Semi parametric model is found to be perform well.

Bowden and Payne	Marginal Hourly real time price of five hubs	Midwest Independent System Operator	• ARIMA • ARIMA- EGARCH • ARIMA-EGARCH-M	RMSE, MAE,MAPE, Theil's inequality coeffiecient Comparing the performance indices, ARIMA-EGARCH-M is found to be best for all hubs except one.
Kristiansen	Day ahead hourly electricity prices	Nord pool power market	Auto regressive models with exogenous variables and daily dummy variables	MAPE (around 5%)
Hickey et al	Hourly spot electricity prices of five hubs	Midwest Independent System Operator	• GARCH • EGARCH • APARCH • CGARCH	MAE,MSE APARCH outperformed all other models in all hubs

Table.2.1.Major works in short term electricity Price forecasting

A study of various models used for electricity price forecasting reveals that ARIMA and GARCH models are generally used for short term price forecasting and almost all other models are compared with these models. Even though the other models are found to be slightly better than ARIMA and GARCH model, their computational complexity is very high and hence they cannot be used in a generalized way. Therefore, there is a need for another model with better accuracy, less computational burden and which can be used as a universal method.

2.5.Literature Review on Sliding Mode (SM) Control:

Variable structure systems (VSSs) with a SM were first proposed in the 1950s [71]. However, due to the difficulties associated with practical implementation, SM Controllers were not widely accepted until 1970's. Many methods are deployed to address the difficulties due to high-frequency switching and now a days, SM Controller's are widely used in a variety of application areas, such as in general motion control applications and robotics, in process control, in aerospace applications, in power converters, and recently in financial markets [72]. This widespread popularity of SM Controller is because of its properties such as robustness, good control performance for nonlinear systems, and applicability to multiple-input–multiple- output (MIMO) systems. The major advantage of SM Controller is that when a system is in a sliding mode, it is insensitive to parameter changes or external disturbances.

There are some difficulties associated with SM Controller's when implemented in a practical environment. The main difficulty is chattering. Chattering is the high-frequency oscillations of the controller output resulted from the high-speed switching of the controller.

The chattering may excite un-modeled high-frequency plant dynamics. Another difficulty is the vulnerable nature of SM Controller to measurement noise. To overcome parametric uncertainties the SM Controller may employ large control signals which are difficult to apply in practice. To alleviate all these difficulties, several modifications to the original sliding control law have been proposed by many researchers.

One of the methods proposed is the fusion of soft-computing methodologies in SM control. Conversely, the fusion of soft computing techniques in SM Controller requires rigorous design and has to ensure the stability. This method provides an extensive freedom for control engineers to make the most of their perception of the problem. Hence, there is a growing amount of interest in the use soft-computing methodologies in SM Controllers.

2.6. Conclusions:

From the literature review it is evident that researchers have proposed many methods and techniques to address the stability issues of bidding dynamics in Electricity market. Most of the proposed methods address the energy markets in developed countries. Issues faced by energy markets in developing countries are very different from that of developed countries. Hence, a proper system analysis of energy market in developing country is needed to stabilize the system.

Electricity price forecasting is still at its developing stage. Time series models, artificial models, game theory models, and simulation models are generally employed to forecast the electricity prices. Still, there is a deficit of a method to model the electricity price fluctuations in developing country.

Sliding mode control theory outperforms the other control methods in every nook and corner of practical applications such as industrial applications, aerospace applications, robotics, and financial applications. Even though there are some difficulties associated with sliding mode control, researchers are now proposing fusion of soft computing techniques with sliding mode control to alleviate the practical difficulties in sliding mode control design.

Chapter 3
Electricity Market Bidding Dynamics- Block Diagram Approach

3.1.Introduction

Many research works discuss the principles, theory, problems, and experiences of power pools. Out of these, some research works offer the solutions to the problems by carrying out the mathematical analysis of such systems. In this, the major emphasis of the mathematical analysis is based on optimization. Such optimization problems are formulated using the principles of game theory. The main drawback with game theory lies in the discrete nature of the state. Still, the theory is employed for small systems. But, it is computationally expensive for large systems. In this context, control system principles are adopted for obtaining the solution.

As said above, bidding system is represented as a control problem in [1] and applied classical control techniques. The objective of that work was to investigate the effect of introducing feedback into the bidding process or more precisely, the effect of introducing bidding rounds. The general principle of feedback reduces uncertainty, which is the core reason for approaching generation bidding as a control problem. Bid selection is a non-linear process and as such its output can be considered uncertain. Also, the effect of individual generator actions on the system as a whole is uncertain and the generators themselves are uncertain as to their best bid. In the analysis, it is assumed that producers do not attempt to manipulate the bidding process (e.g., collusion between producers to ensure that supply does not exceed demand and hence inflate the marginal price). Investigation of such issues is a topic for future research. Since the classical control techniques like Proportional Integral Derivative (PID) control techniques are not appropriate to implement in the financial environment, further studies are not carried out in this perspective.

This chapter is organized as follows. Section 3.2 gives a general introduction to the economic structure of electricity markets. In Section 3.3, the bidding process is expressed as a control problem. In section 3.4., the bidding dynamics in an electricity market is presented as a block diagram. The different blocks in the process such as electricity price forecasting, regulatory model, negotiation model for bilateral contract and the core of bidding process, bid selection procedure and the control aspect of adjustment of producer’s bid are explained in detail in section 3.4. Section 3.5 discusses the concluding remarks of electricity market bidding dynamics expressed in a control perspective.

3.2.The Economic Structures of Electricity Market:

In the economic perspective, the electricity market structure can be divided into monopoly, oligopoly and perfectly competitive market. During the deregulation process, the vertically integrated monopoly market is transformed finally into a perfectly competitive market. In most of the developing countries, the market is in the oligopoly state. The table 3.1.gives a comparative study of different economic structures of the electricity market.

Characteristics	Market structure		
	Monopoly	Oligopoly	Perfect Competition
Buyer number	Many	Many	Many
Seller number	One	Few	Many
Buyer Entry Barriers	No	No	No
Seller Entry Barriers	Yes	Yes	No
Pricing	Price Maker	Price maker	Price taker
Economic Efficiency	Low	Low	High
Innovative behaviour	Potentially strong	Very strong	Weak

Table 3.1.Economic structures of Electricity Market

In a perfectly competitive market, the number of producers is large enough and they are at the same level in terms of sales, all are price takers in such a way that no one has the market power to affect the market price by changing its strategies. 'The price taking producer' is a small part of the industry and its own activities could not affect the market price. There is no barrier to entering into this market for sellers or buyers and hence they can enter or exit the market very easily. Moreover, all the market information concerning the price, production, and cost are known to each market participants.

On the converse, in a monopolistic market, there is only one seller, who is able to provide the entire electricity supply and to operate the market. In this case, the entry of a new seller is highly restricted in such a way that there is no substituting commodity.

In between these two states, the oligopolistic market is dominated by a few large companies instead of a single one. The number of companies in a market is few if one company's decisions have a significant influence on the profit of other companies. Hence, the producer's decisions are interdependent. The market entry restriction is also high compared to the perfectly competitive market. The deregulated electricity market is mostly like an oligopolistic market, within which the generation companies develop strategic planning and bidding by taking into account others' behaviours.

3.3.Bidding Process as a Control Problem:

The market clearing price (MCP) is defined as the price of a good or service at which quantity supplied is equal to the quantity demanded. Hence, MCP is otherwise known as the equilibrium price. Equilibrium price is actually an ideal concept as at this price the exact quantity that producers take to market will be bought by consumers, and nothing will be 'left over'. This is efficient because there is neither an excess of supply and wasted output, nor a shortage and the market clears efficiently.

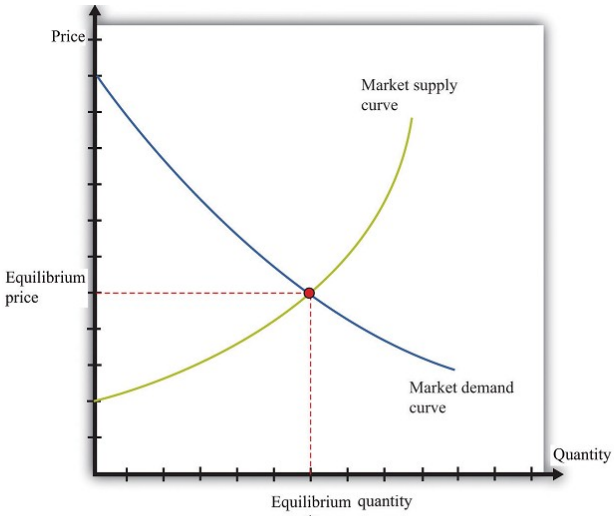

Fig.3.1. Determination of Market clearing price/Equilibrium price

From, the theory of economics, the equilibrium price is given by the point at which supply and demand curves meet as shown in fig.3.1. In an oligopoly electricity market, the bidding process tries to find the equilibrium price by analyzing the bids or in general supply available and the demand requirements.

At the most basic level, the bidding process consists of an independent system operator (ISO) which announces the required load. Using this information, the individual generating units submit bids to the ISO. By selecting the most competitive bids, the ISO will determine the MCP.

In an oligopoly market, only minimal information is available to the individual generators. For example, generators do not know about the price curves of other generators. Hence there will be a mismatch between demand and supply. Therefore by introducing the concept of the control system, the bidding process can be modelled as shown in fig.3.2.

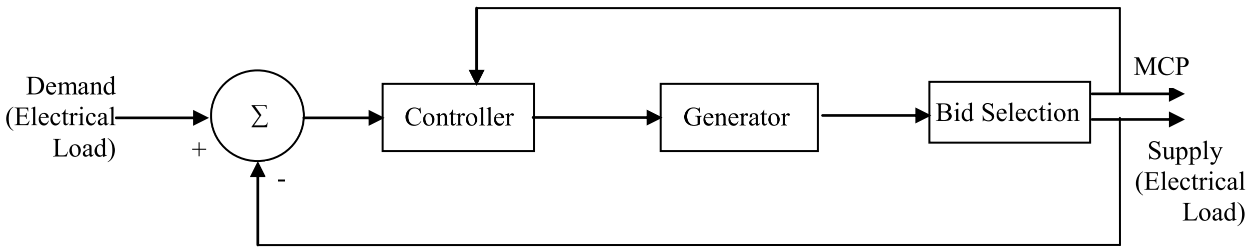

Fig.3.2.Bidding Dynamics as a Control Problem

In the bidding system, the bids are selected to meet the required volume, at the same time minimizing the purchase cost. Whenever there is a mismatch between the supply and the demand, the controller will adjust the generator bids accordingly. The process is repeated to ensure supply equals demand.

3.4.Bidding Dynamics: Block Diagram Representation

In mixed pool/bilateral electricity markets, participants can sign forward bilateral contracts for several months in advance of its delivery. Besides, generators may sell electrical energy and consumers may buy electrical energy from the pool at the spot price through the Day Ahead Market (DAM) or balancing markets. In both cases, the market participants should get an idea about the volume/load and price expected during the days. The electricity market bidding dynamics in a mixed pool/bilateral electricity market is modelled as shown in the block diagram in fig.3.3.

Since the electricity load forecasting is at its saturated stage, the forecasted load is treated as a known quantity. Initially, from the historical data, the electricity prices are forecasted using a chaotic model approach derived from the time series analysis. The electricity prices are given as inputs to the power exchange players.

Bilateral contracts are generally used in electricity markets to hedge against price volatility. If the contract is not chosen properly, the MCP will end up in either low or high price compared with the contract price. One of the main contributions of this work is to propose a negotiation strategy termed as Buyer Motivated Negotiation Strategy (BMNS) which is based on the demand response actions. Seller agent and buyer agent using the BMNS strategy agree upon to deliver a fixed quantity at a fixed price.

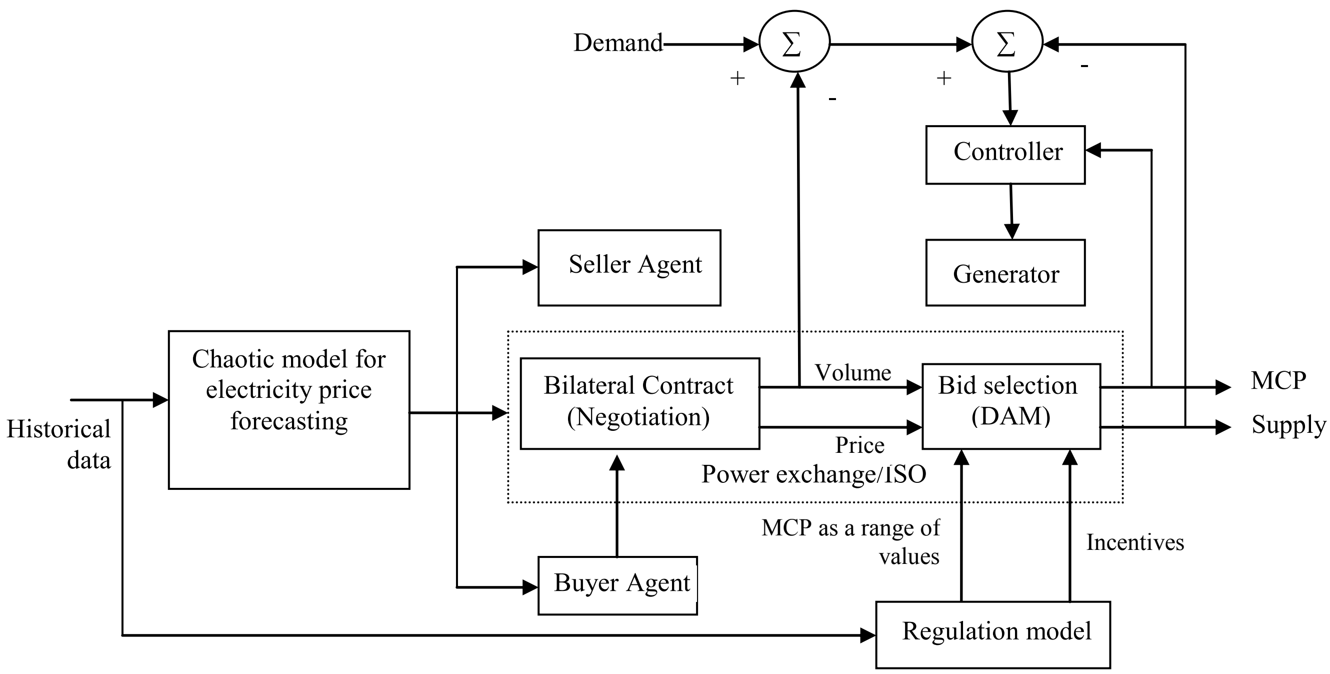

Fig.3.3. Block Diagram Approach – Electricity Market Bidding Dynamics

Since the electricity market cannot mimic the economic signals as in the case of other financial markets, regulation is necessary to ensure the social welfare. The scope of Profit Ceiling Model (PCM), the latest trend in the financial market, is analyzed in the context of the electricity market is another contribution of this work. The uplift forecast, the major concern associated with PCM is treated as an optimization problem and solved using the hybrid GPSO method. The PCM will determine the MCP as a range of values. The investors are entertained by giving incentives and the incentive mechanism is very beneficial for the healthy development of electricity markets in developing countries.

From the submitted bids, the ISO will choose the most appropriate one and fix the market clearing price (MCP) accordingly. If there is any mismatch between supply and demand the controller will adjust the bidding parameters, in turn, the generation parameters consequently. Instead of the usual Proportional Integral (PI) controller, sliding mode controller is found to be effective in stabilizing the chaos present in the bidding dynamics. The sliding mode controller parameters are tuned with the hybrid GPSO algorithm.

3.5.Conclusions:

In this chapter, the bidding process is formulated as a control problem by introducing the concept of feedback. The mechanism is based on inflating the marginal prices and ensuring the supply nearly equal to demand. The entire mechanism in electricity market bidding dynamics such as electricity price forecasting, regulation aspects, bilateral contract negotiation, and the bidding process is modeled in a single block diagram. This block diagram approach is the platform from where the whole research contributions are tapped out.

In the existing literature, the majority of works related to bidding dynamics in the electricity market is based on the concept of game theory. The major drawback of game theory based solution is that it is based on discrete states, which makes larger problems computationally expensive. Hence, a new approach is formulated in which the bidding process is transformed as a control problem in 2000[1]. Even though, some classical control techniques are suggested to address the problem, due to the difficulty of implementation of PID controllers in financial environment that area of research is not flourished further.

The major contribution mentioned in this chapter is treating the bidding dynamics employing block diagram representation. In this approach, all the basic elements of electricity market bidding dynamics are incorporated and a sliding mode controller is suggested to control the producer's strategic bid adjustment. The sliding mode control implementation is found to be very appropriate in dealing the financial environment.

CHAPTER 4
Design of a Chaotic Model for Electricity Price Forecasting

4.1. Introduction:

After the restructuring of electric power industry, different entities in the field namely generation companies and consumers decide the electricity price, specifically market clearing price (MCP) [74]. Electricity price forecasting is considered to be a decisive issue for the market participants around the globe in the present deregulated scenario. It has now emerged as one of the major research fields in electrical engineering. An accurate price forecasting helps the suppliers to determine the bidding strategies make decisions on investments and in making them cautious about the risks involved in the bidding process. On the other hand, the consumers use price forecasting techniques to exploit the purchasing strategies for their maximum utilization [75]. Motivated by these practical aspects, many researchers developed tools and algorithms for load and price forecasting. Among these, load forecasting techniques are in the advanced stage of development such that algorithms with mean absolute percentage error (MAPE) below 3% are available in the literature [76]. Even though price forecasting techniques are being applied, they are still in their infant stage of development, due to the extreme volatility of price curves compared with load curves. Besides the extreme volatility, the electricity market prices are characterized by high frequency fluctuations, variable mean and variance and calendar effects. The major reasons for all these unusual characteristics of price curves in electricity market compared with other financial markets are due to non storable nature of electricity, inelastic nature of demand in a short period of time and the oligopoly market [77].

Electricity price forecasting can be classified into long term objective (future investment on power plants), medium term objective (risk management and price derivating) and short term objective (auction type bidding). Unforeseen events of supply shocks such as non availability of fuel resources, constraints on physical infrastructure, load imbalances, climate changes or any other external factors lead to a severe impact on the market clearing prices in a short term perspective. Hence, short term price forecasting is more crucial compared with other objectives. Short term price forecasting techniques are either inspired from electrical engineering or financial econometrics literature. Short term price forecasting may be broadly classified into game theory models, time series and simulation models [78].

In all the models proposed so far except time series model, the model order is generally calculated by employing the autocorrelation of the price series and cross correlation of price with other factors especially with the load. After determining the model order, the different stages in the model identification process are employed to determine the model parameters. However, the highly fluctuated prices and the volatility of the electricity market originated from known and unknown factors are the major reasons for lesser accuracy of the models.

In this perspective, the fundamental question is whether these fluctuations originate from a deterministic, stochastic or a chaotic system. The most general approach to resolve this question is time series analysis. Many methods and techniques are adopted from time series analysis to portray the characteristics of economic markets. They are mainly power spectral density analysis (PSD analysis), test of surrogates and phase space reconstruction [79]. The complexity of stock market specifically its chaotic nature[80],Chaos in stock returns[81],Chaos in the composite index of NYSE[82], Heterogeneous models in economics [83], and Chaotic models in macroeconomics[84] are some of the research papers depicting the relevance of chaos in financial markets.

Lately, the chaos theory is also used to solve the complexity of electricity price and add weighted one rank multistep prediction model [85] is used to forecast the electricity price. In the paper referred above, the chaotic property is identified with positive MAXIMAL Lyapunov exponent only, but according to chaos theory there is no single method to predict the chaotic nature of a system.

To formulate a chaotic model for forecasting electricity prices in developing country, the datas from Indian Energy exchange is taken as an example. In the framework of deregulation, trading is made as a separate and distinct activity as per Indian Electricity Act 2003. Two power exchanges had started their functioning, namely Indian Energy Exchange (IEX) and Power Exchange of India Ltd. (PXIL) in June 2008 and October 2008 respectively. IEX is the leading power exchange with more than 97% of electric power traded through its day ahead spot market. Day-ahead market (DAM) is a physical electric trading market for deliveries of next day starting from midnight in 15 minute time blocks [86, 87]. So far, only two studies are carried out in forecasting Day-Ahead Market MCP in Indian scenario. Other than the Artificial Neural Network model, MSARIMA-EGARCH model was also developed to predict the MCP [88]. Motivated by this background, the properties of MCP in Indian Electricity market is analyzed considering time series data for one month, specifically IEX day ahead market clearing price for September 2013. The results of these analyses highlight the existence of chaos in the time series data as well as the seasonality and non stationarity in the system dynamics. Moreover, the forecasting results imply that a fixed model cannot predict the system behaviour accurately and hence the developed model should be updated regularly.

This chapter is organized as follows. In section 4.2, Characteristics of chaotic systems are presented. In section 4.3, MCP of IEX is analyzed and its chaotic nature is identified. In section 4.4, the reconstruction of phase space is described. In section 4.5, add weighted one rank multistep prediction model is described. Simulation results are shown in section 4.6. Finally, conclusion is presented in section 4.7.

4.2. Characteristics of Chaotic Behavior of Time Series Data:

Chaotic behaviour of systems is identified in almost all walk of scientific discipline such as biology, chemistry, physics, engineering, social sciences, economics etc. Chaotic systems are basically nonlinear deterministic systems which are very sensitive to initial conditions and hence prediction of their future behaviour/responses is almost impossible. Even though, the system responses are random in nature, they were generally treated as deterministic process. Using the basis of chaos theory, deterministic rules can be manipulated from highly fluctuated chaotic behaviour of the systems. In other words, chaotic techniques may be used to explore the system's inherent dynamics, which is generally nonlinear in nature and hence may be applied to discriminate from the random processes. This exploration of dynamics of a real system facilitates to forecast the nature of the system irrespective of the complex fluctuations in its characteristics.

Chaotic behaviour of a system places different hallmarks in the system characteristics. The major hallmarks/features of chaotic systems are existence of chaotic attractors, sensitivity to initial conditions, bifurcations and Positive Lyapunov exponent. Different methods and techniques have been developed to identify the chaotic properties of the system either from the dynamic model of the system or from the system outputs obtained from experiments. If the system's dynamic model/mathematical description of the system dynamics is readily available, the features can be examined using the well developed techniques presented in the literature. On the other hand, for most of the real time systems only a limited time series data as system output may be available instead of a reliable dynamic model. Since the time series data available from real system are generally noisy in nature, it may be difficult to extract the features of the system and hence complex time series analysis may be applied to the same. The different time series analysis techniques to identify existence of chaos in a system are generally the power spectrum density analysis, surrogate data, determination of Lyapunov exponent and phase space reconstruction [89].

The existence of strange attractor and low fractal dimension are the major features of presence of chaos in a real dynamical system. The state trajectories of a chaotic dynamical system will generally converge to a strange attractor. The fractal dimension of this attractor counts the effective number of degrees of freedom in the dynamical system and thus quantifies the system's complexity. To determine the fractal dimension of a dynamical system, the first step is the determination of time delay and embedding dimension of the system. The time delay can be obtained through evaluation of the autocorrelation function and/or average mutual information. The embedding dimension is related to the minimum number of independent variables necessary to describe the system. A strange attractor could also be revealed in a chaotic system under phase space reconstruction. An exponentially decaying power spectrum is another characteristic of existence of chaos. Another hallmark of a chaotic dynamic system is the sensitivity of system’s behaviour to initial conditions. The sensitivity to initial condition is usually quantified in terms of Lyapunov exponent. The Lyapunov exponent measures the rate of exponential divergence of nearby trajectories. A positive Lyapunov exponent ensures the existence of a chaos in the real system. The surrogate data testing can identify the existence of pure random process and thus help to reject the presence a chaotic system [90].

4.3.Experimental Data Analysis and Identification of Chaotic nature:

4.3.1.Overview of IEX Data:

India is a power deficit country and sometimes there is a wide gap between demand and supply. This is in contradiction to other developed countries like UK and Nordpool, which operates in power surplus. Hence India adopted a power pool model i.e. different generating companies selling to a pool and distributers or large consumers buying from it. So the pool functions as a market place for trading.

The two power exchanges in India started their functioning in 2008, they are Indian Energy Exchange (IEX), and Power Exchange of India Ltd (PXIL). However, more than 95% of power traded in India is through IEX. Fig.4.1. shows the comparison of total power generated in India from 2009 -2013 to the volume of power transacted through IEX.

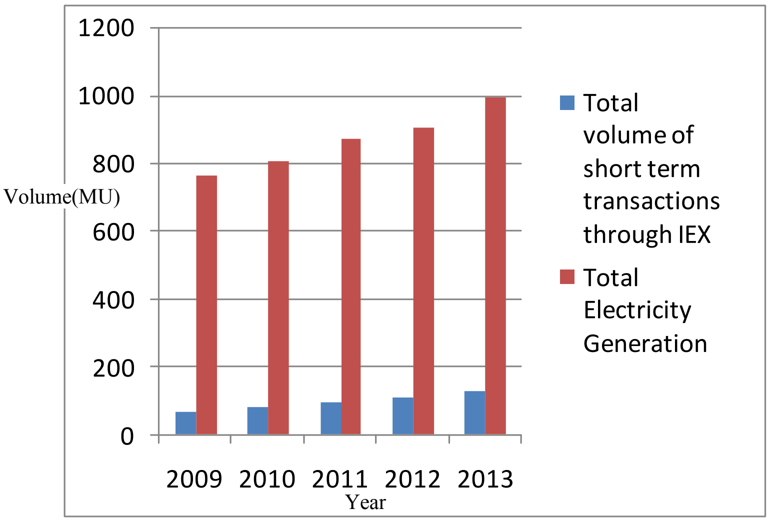

Fig.4.1. Comparison of Total volume of short term transactions and total Electricity generation in India

Fig.4.2 and fig.4.3. show the volume and price of electricity transacted through day ahead market. From the figure it is evident that the volume transacted became equal to zero on July 30th 2012. This occurs due to the major grid disturbance in northern region. From the figure, it may be concluded that the electricity price fluctuations are very high in developing countries where the physical infrastructure is not compatible as in the case of developed countries.

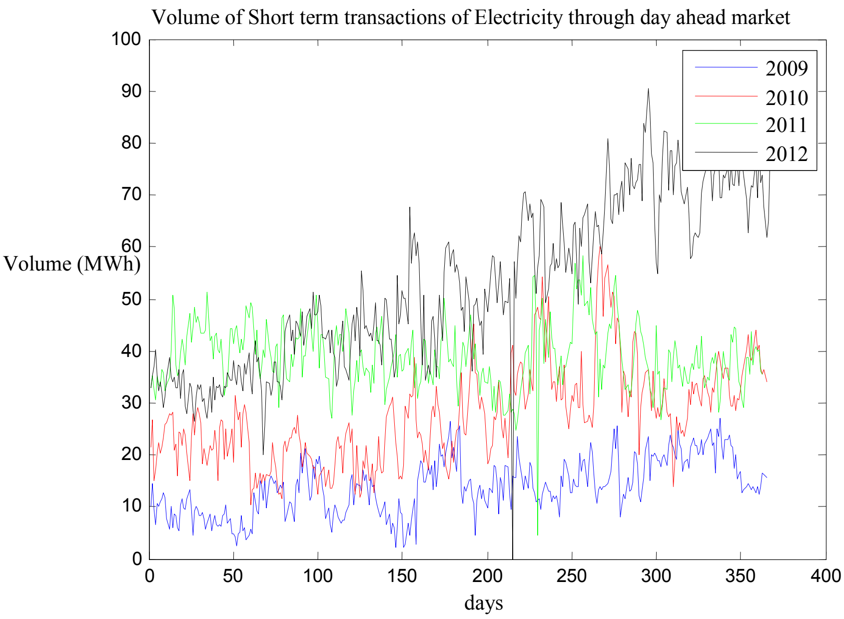

Fig.4.2. Volume of short term transactions of Electricity through IEX

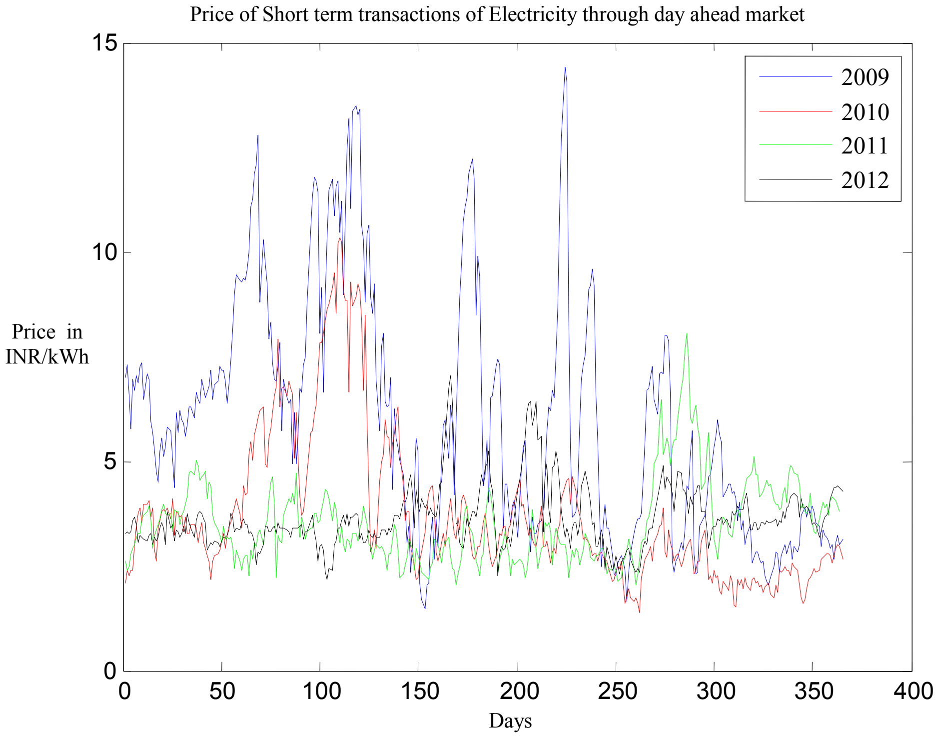

Fig.4.3. Price of Electricity transactions through IEX

Market clearing price (MCP) is given by the intersection of total demand curve and the total supply curve, for a particular time. Real time data on MCP is collected from IEX. The present study focuses on a particular time frame, September 2013. This period is chosen since the price curve exhibits high volatility during this time frame. The seasonal variations and trends are embedded in such a way that the data set appears in random order. The statistics of data considered for analysis is summarized in table 4.1 and it is evident that the time series is not normally distributed and negatively skewed.

Mean	Median	Max	Min	Std.dev.	Skewness	Kurtosis	Jarque Bera Test	No of Observations
4177.2	2999.9	8510.1	2027.9	1153.9	-0.76	0.10953	75.04	2871

Table 4.1: Electricity Price in Sept 2013- Statistics Summary

Skewness is a measure of symmetry, or more precisely, the lack of symmetry. Kurtosis is a measure of whether the data are heavy-tailed or light-tailed relative to a normal distribution. Jarque Bera test is a goodness of fit test to check whether the kurtosis and skewness match with that of a normal distribution values. The tabulated values indicate stronger peaks, rapid decays and heavier tails. In general, all these values indicate the high volatility of electricity prices.

4.3.2.Identification of Chaotic Nature using Power Spectral Density:

Power Spectral Density (PSD) shows the strength of variations (energy) as a function of frequency. Intuitively, the spectral density captures the frequency content of a stochastic process or time series, and helps to identify the periodicities.

The exponential decaying characteristic was universally found in the power spectral density of all chaotic time series data irrespective of data length as well as time range of data [91]. The other two structural features which are useful to distinguish the chaotic signals from non chaotic are the sharp peaks and broad band noise in the PSD. To estimate the PSD, the periodogram method of calculation of power spectral density is employed. Since the power spectral density of a continuous function defined on the entire data set is the modulus squared of its Fourier transform, the simplest technique to estimate the spectrum is the periodogram which is also given by the modulus squared of the discrete Fourier transform. The power spectral density of time series data is shown in the fig.4.4. From the PSD, it is evident that the data obtained from IEX is chaotic in nature.

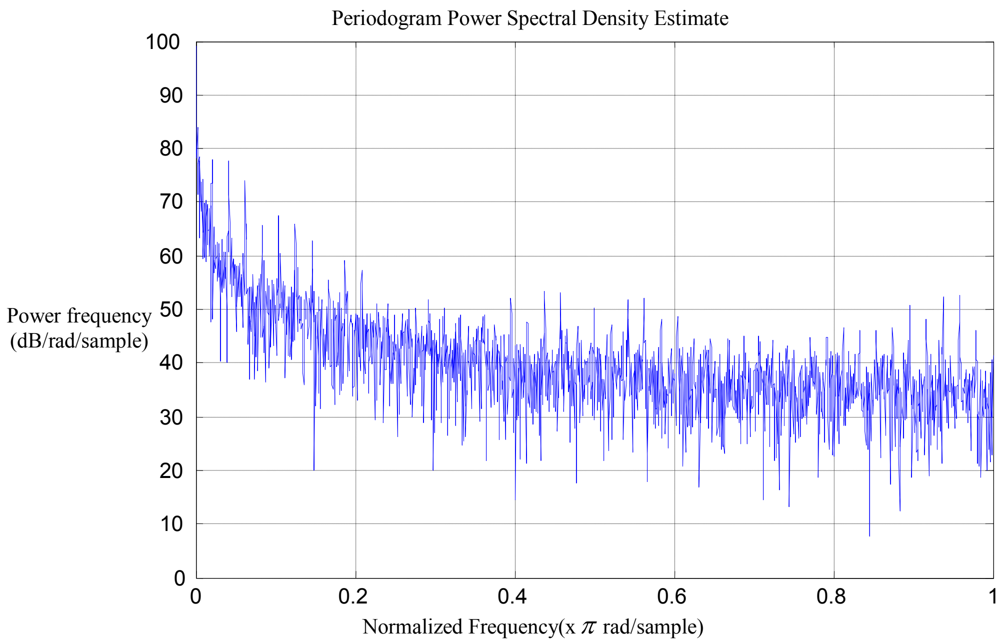

Fig.4.4.Power Spectral Density (PSD) of MCP

4.3.3.Identification of Chaotic Nature using Surrogate Data:

Surrogate data is produced by phase randomizing of the original time series. It has similar spectral properties as of the original data i.e., the surrogate data sequence has the same mean, variance and same autocorrelation function. Hence the original and surrogate data have the same power spectrum and the only difference is the phase relations may be destroyed [92]. The surrogate data of MCP is shown in Fig.4.5.

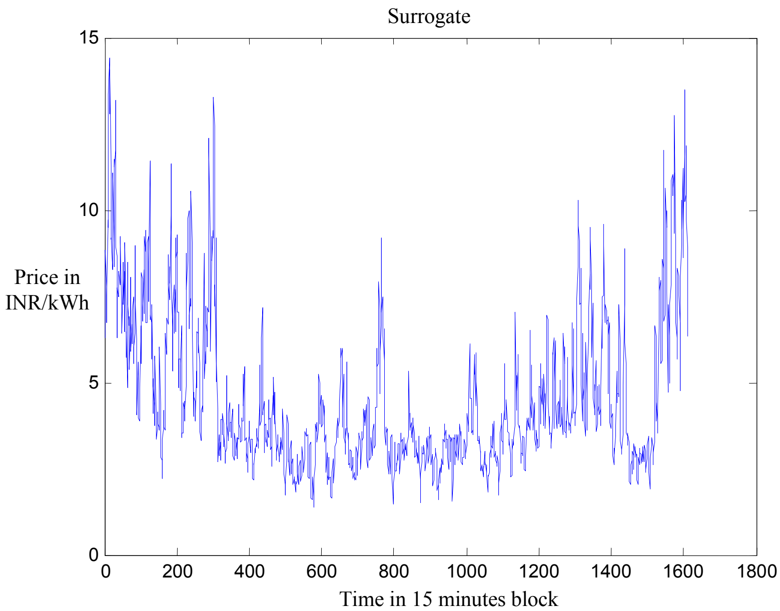

Fig.4.5.Surrogate data of MCP

The generated surrogate data is compared to the original data under a nonlinear discriminating static in order to reject/approve the null hypothesis. In the proposed analysis, the null hypothesis is chosen such that if the discriminating metric of original data is less than that of surrogate data it indicates the presence of chaos in the dynamic time series data. The discriminating metric of surrogate data is obtained as 0.785, which is higher than 0.247 the discriminating metric of the original data indicating the presence of chaos in the time series.

4.3.4.Identification of Chaotic Nature using Positive MAXIMA Lyapunov Exponent:

Another hallmark of chaotic systems is the positive MAXIMAL Lyapunov exponent. The method of Lyapunov exponent approach is based on the idea that the distance between two nearby orbits of attractors grow exponentially with time. Lyapunov exponent is a quantitative measure of this feature of chaotic systems. If the Lyapunov exponent is greater than zero, the time series under consideration is chaotic in nature. Among the different methods proposed in the literature to estimate the Lyapunov exponent, the method suggested by Derbyshire and Broohead (DB method), which shows better performance in the presence of noise is used in this work. Using DB method, the Lyapunov exponent for the MCP of IEX is obtained as 0.598, which is greater than zero and it is a clear indication of chaotic nature of the electricity price.

The analysis of the MCP data taken from IEX indicates the presence of chaos because the time series data exhibits very sharp peaks with exponential decaying PSD, positive Lyapunov exponent and test of surrogates. Hence, a proper chaotic model can incorporate the highly volatile nature of MCP. Chaos theory suggests the phase reconstruction theory for the development of chaotic model.

4.4.Phase Space Reconstruction of the MCP:

Generally, a chaotic time series can be embedded into phase space by Taren's embedding theorem. Let $x_n, 1 \le n \le N$ be the chaotic time series, it can be embedded into the reconstructed phase space with an embedding dimension m and time delay τ. A point in the reconstructed phase space is given by,

$$\mathbf{x}_n = \begin{bmatrix} x_n & x_{n-1} & . & . & . & x_{n-(m-1)\tau} \end{bmatrix}^T \tag{4.1}$$

To reconstruct the phase space two parameters have to be determined. They are the embedding dimension (m) and time delay (τ). There are many methods available to determine m and τ.

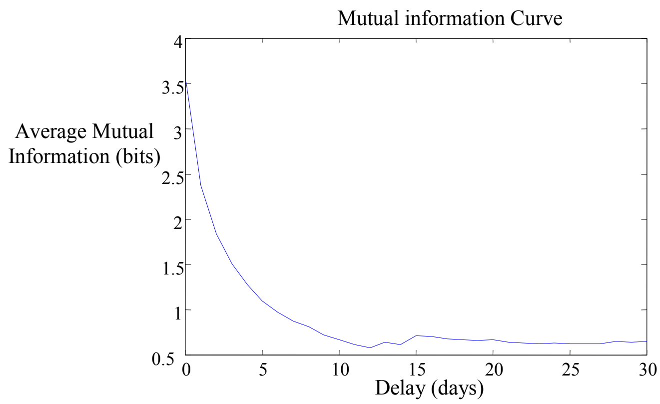

Fig.4.6. Mutual information versus time lag for determination of time delay

However, the selection of different methods depends on the optimal embedding dimension and embedding window width. One of the optimal combinations is mutual information approach to determine τ and false nearest neighbour method to determine embedding dimension m.

The mutual information approach provides the nonlinear dependence between successive points. If the delay time τ is taken as the first minimum of mutual information, then the state vector will consist of variables that possess minimal information between them. The fig.4.7 shows the mutual information curve for the time series data, and the first minimum mutual information is obtained as 11.75. Hence the corresponding time delay is chosen as $\tau = 11$ using truncation.

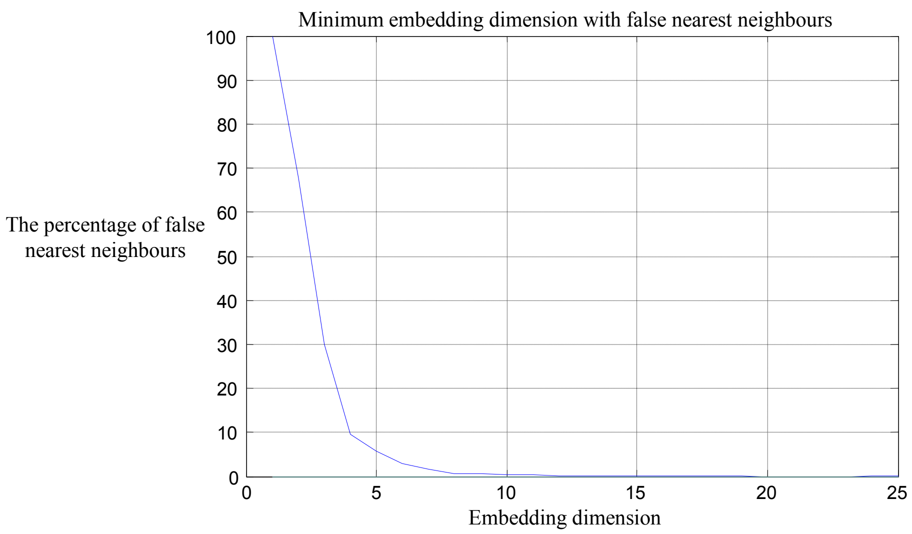

Fig.4.7.Percentage of False nearest neighbour as a function of embedding dimension to determine the embedding dimension

A well known method to determine the minimal sufficient embedding dimension is the false nearest neighbour method [93]. In false neighbour method, the topological structure cannot be preserved in case of wrong embedding dimension and thus creating false neighbours. The embedding dimension with minimum false neighbours will map the original neighbours into the neighbours in the reconstructed phase space also. Using this method, the embedding dimension with minimum false neighbours can be determined from the fig 4.7. as $m = 9$.

4.5.Chaotic Model for Price Forecasting:

Add-weighted one rank multi step prediction model is used to forecast electricity price based on phase space reconstruction technique [85].Let the present state be X_M and the states near the preset state be $X_{Mi}; i = 1,2,...,q$ .The weighting of X_{Mi} as in[85] is given by,

$$P_i = \frac{\exp\left(-c\left(d_i - d_m\right)\right)}{\sum_{i=1}^{q} \exp\left(-c\left(d_i - d_m\right)\right)}, \tag{4.2}$$

where c is a constant and generally equals to 1, d_i is the distance between X_M and X_{Mi} and d_m is the minimum distance in d_i.

Then the k th step predictive value is given by,

$$X_{M+k} = a_k e + b_k X_M \tag{4.3}$$

Where

$$e = [1 \quad 1 \quad . \quad . \quad . \quad 1]^T \tag{4.4}$$

and

$$\begin{pmatrix} a_k \\ b_k \end{pmatrix} = \begin{pmatrix} \alpha & \beta \\ m & \alpha \end{pmatrix}^{-1} \begin{pmatrix} e_k \\ f_k \end{pmatrix} \tag{4.5}$$

$$\alpha = \sum_{i=1}^{q} P_i \sum_{j}^{m} X_{Mi}^{j}$$

$$\beta = \sum_{i=1}^{q} P_i \sum_{j}^{m} \left(X_{Mi}^{j}\right)^2$$

$$e_k = \sum_{i=1}^{q} P_i \sum_{j}^{m} X_{Mi+k}^{j} X_{Mi}^{j}$$

$$f_k = \sum_{i=1}^{q} P_i \sum_{j}^{m} X_{Mi+k}^{j} \tag{4.6}$$

X_{Mi}^{j} is the j th element of X_{Mi}. With this algorithm, the chaotic model of the IEX MCP is constructed for the time domain, September 2013. This chaotic model is used to forecast the MCP for next day.

4.6.Simulation Result and Analysis:

By using the developed chaotic model, DAM MCP for IEX is predicted. The simulation results for October 2013 are shown in fig.4.8. The actual and forecasting price with chaotic model, ARIMA model and GARCH model are shown in the figure.

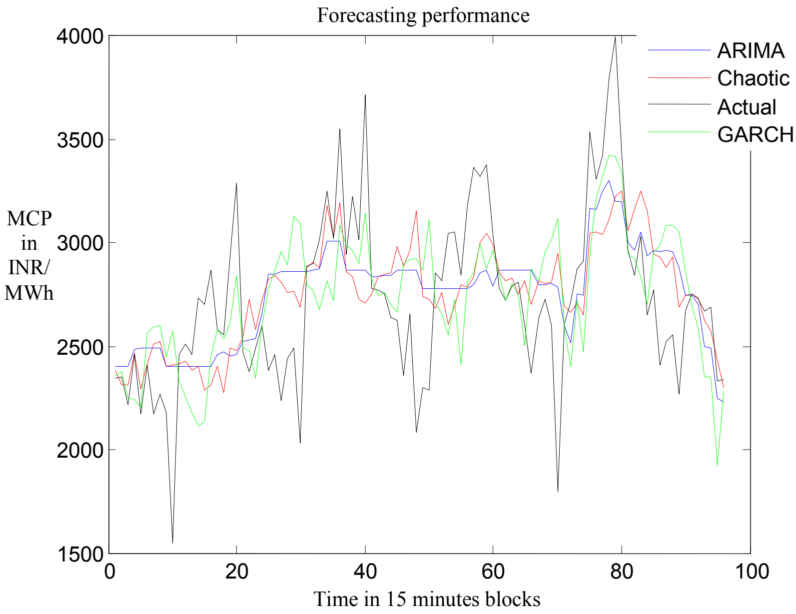

Fig.4.8. MCP Prediction for October 2013 using different model

Model	ARIMA	GARCH	Chaotic Model
RMSE	2185	2206	588
MAE	1119	1118	372
MAPE	8.971	8.859	5.071
Variance proportion	0.0597	0.063	0.049
Bias proportion	0.0065	0.0055	0.0051
Theil inequality	0.0456	0.0445	0.0395

Table 4.2: Comparison of different models in predicting the MCP

The forecasts are evaluated using standard performance criteria such as Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Bias and Variance Proportions and Theil inequality coefficient. MAE and RMSE depend on the scale of variable, while MAPE and Theil inequality are insensitive to the scale of variable. The errors are tabulated in table 4.2. Forecasting performance is better for the model, whose error is smaller. From the results, it is evident that the chaotic model is a good candidate for the DAM MCP of IEX over GARCH and ARIMA models. The major advantage of this model is that the computation complexity is reduced and hence computational time is less and its adaptability is very strong.

4.7.Conclusions:

Short term Electricity price forecasting in the case of organized power exchanges in developing nations is one of the directions of future research. There are very few studies related to the short term electricity price forecasting for developing countries where electricity markets are getting deregulated. The chaotic nature of market prices is investigated and the developed chaotic model is compared with other forecasting models like Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. The simulation results demonstrate the efficacy of the proposed model for short term price forecasting in Indian scenario over the other methods in terms of accuracy, computational complexity, and adaptability.

In the existing literature, many methods are available for electricity price forecasting. Among these methods, time series methods are found to be effective over other methods. Some research works report that high volatile time series may be predicted with chaos theory. Phase space reconstruction based on chaos theory is suggested in the literature. Using this theoretical background a chaotic model namely add weighted one rank multistep prediction model is developed for the electricity price forecasting for the developing countries, like India.

Chapter 5
Design of a Buyer Motivated Negotiation strategy

5.1.Introduction:

In the restructured power industry, the generation companies /suppliers and distributers/buyers trade through both power pool and bilateral contracts. A bilateral contract is a mutual agreement between suppliers and buyers to exchange electric power under a set of specified conditions such as time of delivery, duration, MW amount, and price [94]. Even though the bilateral contracts can be considered as future/forward contracts, they can be generally traded until their time of delivery in an exchange. On the other hand, forward/future contracts are generally remaining fixed after the negotiation process between the concerned parties. Bilateral contracts can take the form of futures or forward contracts, where the former are generally traded in an exchange [95], and can be traded continuously up until their time of delivery. In contrast, forward contracts are typically negotiated directly between the load and generator with the terms of the contract remaining fixed until the time of delivery [96].

Moreover, a bilateral contract can be either financial or physical. Physical contract means all the power traded through bilateral contract must be self-generated /self-consumed at the specified network buses [97]. On the other hand, the physical contract is similar to the pool where the power is transferred upto the market clearing time. Hence financial contract can be interpreted as a contract of difference which guarantees the difference between the contract price and pool price and has no direct implications on physical transmission.

Bilateral contracts are typically employed in electricity markets to hedge against electricity price volatility. However, if the contract is improperly made, it may worsen the situation and may end up being the market clearing price either too low or high compared to the contract price. Besides the market clearing price volatility, there are other sources of risks associated with the bilateral contract such as load forecast errors, network outages, uncertainties in fuel price.

The participants engaging in bilateral contracts are autonomous, heterogeneous and they usually follow their own interaction strategies. Generating companies pursue strategies which maximize their profit, while end-use customers implement strategies which minimize their electricity cost. Here, customer /buyer strategies are associated with the consumption efficiency. Consumption efficiency may be increased by adopting actions related to the energy conservation concepts, energy management, and judicious use of energy. In this context, demand response management strategies can play an active role in improving the electricity market performance.

Although a variety of techniques that enable the study and simulation of electricity markets in developed countries has emerged during the past few years, these are mostly directed to the analysis of market models and power systems' technical constraints, making them suitable tools to support decisions of market operators and regulators. However, the equally important support of market negotiating players' decisions is being highly neglected. The proposed buyer motivated negotiation strategy model contributes to overcome the existing gap concerning effective and realistic decision support for electricity market negotiating entities. The proposed method is validated by realistic electricity market simulations using real data from the Indian Energy exchange(IEX). Results show that the proposed decision support buyer motivated negotiation strategy enable electricity market players to improve their outcomes from bilateral contracts' negotiations.

This chapter is organized as follows. In section 5.2, Concept and Characteristics of the bilateral contract are presented. In section 5.3, the concept of demand response is introduced. In section 5.4, the design of buyer motivated negotiation strategy is described. In section 5.5, Simulation results are discussed. Finally, the conclusion is presented in section 5.6.

5.2.Bilateral Contract:

Pool prices or day ahead market prices exhibit a set of characteristics such as non-stationary mean and variance, calendar effect, multiple seasonality, high outliers, and high volatility. They tend to change quickly and variations are usually highly unpredictable. In this way, market participants often enter into bilateral contracts to hedge against pool price volatility.

A bilateral trading involves only two parties: a buyer agent and a seller agent. The bilateral transaction can be divided into different classes based on the quantities to be traded and the amount of time available before the actual delivery time. These classes are as follows:

(1)Customized long-term contracts: These contracts generally involve large amounts of power (hundreds/ thousands of MW) over long periods of time (several months to years). In this contract, the terms and conditions are set without considering the market operator. However, the operator should confirm that adequate transmission capacity exists for the transactions to be completed within the specified time limit and should ensure the transmission security. The major advantage of this type of contracts is flexibility. On the other hand, the cost of negotiation and the risk involved are the major drawbacks of these contracts.

(ii) Trading “over the counter”: This type of transaction involves delivery of small amount of energy in accordance with a standard profile. The standard profile indicates the amount of energy to be delivered during different periods of the day. This transaction is generally done to refine the position of producers and customers very near to the delivery time

(iii) Electronic trading: In this type, the market participants submit bids to sell energy, or offer to buy energy, electronically. Whenever a new bid is submitted electronically, the corresponding software verifies for a matching offer for the bid’s period of delivery. In the case of a matching offer, a deal is created automatically and the details of offer such as price and quantity are informed to all participants. If no match is found for that particular period, the bid is moved to the list of pending bids and keeps there until it gets a matching offer, or the bid is withdrawn, or it drops because the market closes for that period. This form of trading frequently takes place in the minutes and seconds before the closing of the market as generators and retailers fine-tune their position ahead of the delivery period.

Bilateral contract may be financial or physical and is generally negotiated months or weeks prior to its delivery. The major specifications included in bilateral contract are (i) Constant megawatt(MW) over the length of contract or as specified in blocks of time (ii) constant price per megawatt hour (/MWh) over the length of contract (iii) starting date and time (iv) ending date and time (v) range of hours when the contract is to be delivered. In a more general form, the length of contract, MW and price may be time-varying over the contract duration.

Although a variety of tools are developed to study and the simulation of electricity markets, most of them deals with technical constraints of power system network. Hence these tools are able to support the market operators and regulators only. However, the development of supporting tools for negotiating players is highly neglected. The proposed buyer motivated negotiation model contributes to overcome the existing gap concerning effective and realistic decision support for electricity market negotiating entities. In this work, a new form of bilateral contract negation is formulated based on the demand response strategies.

5.3.Demand Response in Electricity Markets:

Demand response (DR) mostly refers to the changes in electric usage by end-use customers from their normal consumption patterns. These changes in consumption pattern may be in response to (i) changes in the price of electricity over time (ii) to incentive payments deliberated to induce lower electricity use at times of high wholesale market prices (iii) when system reliability is jeopardized [98]. DR programs enable customers to manage their consumption of electricity in response to supply conditions.

Generally, customers employ demand response by adopting one (or more) of three basic set of actions [99]. These actions consist of measures taken by customers to reduce the cost of electricity. In the first set of actions namely foregoing, the customers reduce their electricity usage during the times of high prices without making any change in their consumption pattern in the other periods and this option may result in a discomfort during that period only. These may include actions such as turning off lights by a residential customer, turning off equipments/machineries by a commercial industry. The second set of actions specifically shifting, deals with rescheduling of activities from periods of higher prices to periods of lower prices. This set may consist of actions such as rescheduling of batch production process from evening hours to next day by an industrial customer, delaying of operating washing machine to late night by a residential customer and so on. In the third set, the customers may rely upon their own onsite generation to meet their electricity demand fully or partially. The trend towards renewable energy and micro grid are included in this set of operations.

Based on these actions there are different DR programs such as Incentive based programs and Price based Programs. Incentive based programs are generally established by grid operators or distributors. This program provides incentives to customers for reducing the load and the rate of incentives may be either fixed or time varying. The price based programs are generally employed by suppliers and includes options like time of use pricing, peak hour pricing, real time pricing and so on. The energy markets in Europe, China and several places are now implementing demand response in one or other form.

5.4.Buyer Motivated Negotiation Strategy:

In simple words, negotiation is a process by which two parties try to solve a conflict to realize a mutually beneficial agreement. The negotiation process consists of different phases or stages such as a initiation phase, problem solving phase, and resolution phase [100]. The initiation phase comprises of preparation and planning for negotiation. During this phase, each market player should emphasize the points of difference as well as their positions. A solution for a dispute is found in the problem-solving phase. The major steps during this phase make use of interpersonal interaction, strategic exercises and thus move towards a mutually beneficial agreement. The last phase termed as resolution phase focuses on the implementation of a final agreement. The parties frequently insist a gesticulation of assurance to the agreement (secure the deal) and determine the next procedure once the documents are signed (implement the agreement).

The major features of buyer motivated negotiation model for bilateral contracting in electricity markets are pre-negotiation process and actual negotiation. Pre-negotiation process focuses on the strategic and operational process of preparing and planning for negotiation. Actual negotiation is the heart of negotiation, moving towards an agreement.

5.4.1.Pre - Negotiation:

Pre-negotiation focuses on specifying the activities that should be addressed by buyer and seller agents before starting the actual negotiation process. The major activities to be considered during pre-negotiation process are:

• Identifying the issues to negotiate;

• Prioritizing the issues;

• Defining limits and preferences;

• Selecting an appropriate protocol.

Let A_s and A_b represent seller and buyer agent respectively. Each agent identifies their negotiation issues such as prices and volumes of energy. Let $\left[P_{i\min}^{s} \quad P_{i\max}^{s}\right]$ represents minimum and maximum prices acceptable to A_s and $\left[P_{i\min}^{b} \quad P_{i\max}^{b} \quad V_{i\min}^{b} \quad V_{i\max}^{b}\right]$ represents the range of prices and volumes acceptable to A_b.

The prioritization of the issues means identification of importance of issues or in other words comparison of issues based on their importance.

The negotiation protocol is a group of rules which defines how the negotiation process should progress, specifying when and what actions are allowed. In this work, alternating offers protocol is considered [101]. This is an iterative protocol and includes the iterative exchange of offers and counter-offers. During negotiation process, an agent may accept an offer, send a counteroffer, or end the negotiation. If a counter-offer is submitted, the process is repeated until one of the agents accepts or discards the negotiation process. Hence, A_s and A_b negotiate over issues by alternately proposing offers and counter offers. So only one offer is made per time period, i.e., an agent made offer in odd periods and the other agent made offer during even periods. An offer/ proposal are a vector form specifying a division of the surplus of all the issues. Once a mutually beneficial agreement is reached, the agreed-upon allocations of the prices and volumes are implemented. The agents have the ability to unilaterally opt out of the negotiation when responding to a proposal.

The evaluation of offers is based on the preferences of the agents. The two utility functions, namely the benefit of A_s and cost of A_b are evaluated. After receiving the offer /proposal from the opponent, the agent determines its function. Based on the function value, the agent may decide whether to accept the proposal or to send a counter offer. In this buyer motivated negotiation strategy the negotiation ends when the cost prepared by the buyer is greater than the cost received by the buyer.

5.4.2.Actual Negotiation:

Basically negotiation is the progression of moving towards an agreement. The soul of negotiation is the exchange of offers and counter-offers. The nature of offers, the pattern of offers, timing, the nature, and allowances included are added up to form the fundamental nature of negotiation framework. Negotiation is an iterative process in which an agent changes its parameters and suggests alterations in the opponent’s parameters. With this give and take process, a point at which both parties agreed is reached.

The negotiation protocol describes the states such as sending a counter offer, accepting the proposal etc., the legitimate actions of the agents at particular states such as which type of messages can be sent by whom, to whom and so on, and the proceedings that affect the states such as discard the negotiation process by one agent, accepting the proposal etc. In total, the negotiation protocol defines the turning points at which the agents have to make decisions in accordance with the evaluation of their strategies. Hence at each and every step during the negotiation process, the agents should formulate their strategies and assess the function to choose the appropriate action from all the possibilities. Thus, at each step of negotiation, agents often need to follow their strategies to choose among different possible actions to execute.

The strategies portray the characteristics of the individual agents: sellers and buyers. Both the agents have similar structures, but opposing interests and preferences. Hence two different strategies are developed. Explicitly, the strategy of seller agents is to maximizes their benefit, while buyer agent's strategy are generally equipped a behaviour that minimizes the cost. A brief description of the strategies is as follows.

(i) Seller Strategy /Price management strategy: The aim of seller agent is to maximize its benefit. Hence this strategy can be formulated as a optimization problem to maximize the objective function. The mathematical formulation of the optimization problem is as follows:

$$\text{Maximize, } B^s = \sum_i \left(P_i^s - C_i\right) V_i^b$$

$$\text{Subject to } P_i^s \geq C_i \tag{5.1}$$

where P_i^s is the price proposed by the seller, C_i is the generation cost, V_i^b is the volume proposed by the buyer. The constraint indicates that the cost of generation should not exceed the price proposed by the seller.

(ii) Buyer/volume management strategy: This strategy is based on the concept of DR. Using this strategy, end use consumers can involve in the decision making process of electricity market price. With proper DR actions, the customers can manage their energy consumption especially during peak hours. Accordingly, the customers may respond to the variation of prices by transferring volume from the periods of high prices to periods of lower prices.

The aim of buyer agent is to minimise the cost. Hence it can be formulated as as optimization problem as follows:

$$\text{Minimize } C^b = \sum_i P_i^s V_i^b$$

$$\text{Subject to } V_{i\min} \leq V_i^b \leq V_{i\max}$$

$$\sum_i V_i^b = V_{total}^b \tag{5.2}$$

where, C^b cost to be paid by buyer agent. The constraints assured that the volume offered in each period is within the range of acceptable values and the total volume remains constant.

Besides the volume, the buyer agent negotiates on the price values also. The new prices offered for the next iteration is a function of old price and mathematically given as,

$$P_{i,k}^{b} = P_{i,k-1}^{b} + bP_{i,k-1}^{b} \tag{5.3}$$

Where $P_{i,k}^{b}$ is the price proposed by i^{th} buyer agent during k^{th} step and b is a constant and can be selected suitably.

5.5.Simulation Results and Discussions:

Energy prices and load profile are taken from Indian energy exchange. For simplification purpose assumed that one seller agent and one buyer agent are participating in the negotiation process of bilateral contract. The entire day is divided into 6 periods as follows,

Period 1 :00.00-4.00am
Period 2 : 4.00am-8.00am
Period 3 : 8.00am-12noon
Period 4 : 12 noon-4.00pm
Period 5 : 4.00pm-8.00pm
Period 6 : 8.00pm- 00.00
The table 5.1.shows the initial prices and volumes proposed by the seller and buyer agents.

Agent	Period of day	Price INR/MWh	Limit Price INR/MWh	Volume kWh	Minimum volume kWh	Maximum Volume kWh
Seller	1	4398	3701			
	2	4741	3920			
	3	5901	4892			
	4	5668	4705			
	5	4301	3542			
	6	5712	4698			
Buyer	1	3598	4410	4921	3312	6542
	2	3903	4584	5521	3812	7378
	3	4797	5732	8312	5598	11054
	4	4625	5486	8341	5612	11065
	5	3504	4200	7208	4813	9453
	6	4589	5603	6106	4093	8212

Table5.1.Initial values of volume and price proposed by seller and buyer agents

Negotiation is an iterative exchange of offers and counter-offers. During negotiation, the buyer agent changes its load profile, according to the "Volume Management" strategy, in response to the prices submitted by the seller agent. At the same time, buyer agent adjusts its price values using (5.2).The seller agent adjusts its price values, by means of the "Price Management" Strategy in response to the volume values of buyer.

Cost	1st proposal	2nd proposal	3rd proposal
Received proposal	21024.42	19342.1	19312.3
Ready to send proposal	18112.12	18721.95	19413.51

Table 5.2. Cost values ready to send and proposals received by the buyer agent.

The table 5.2 shows the cost values received proposals and cost values ready to send by the buyer agent. From the table it is evident that during the third proposal, the cost prepared by the buyer agent is greater than the proposal received by the buyer agent. Hence, this proposal is accepted by the buyer agent. Table 5.3 indicates the final proposal (price and volume) accepted by the buyer agent.

Period of day	Price	Volume
1	4453	6539
2	4653	7310
3	5867	5604
4	5435	6712
5	4032	9429
6	5212	4482

Table 5.3. Final proposal accepted by the buyer agent

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From table 5.3., it may be interpretted as the total sum of energy agreed to deliver after the acceptance of final proposal is nearly equal to the initail consumption.

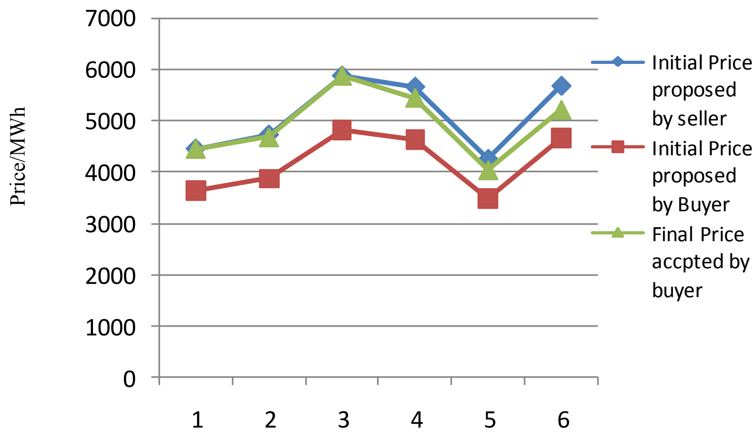

Fig 5.1.Variation of prices during the negotiation process

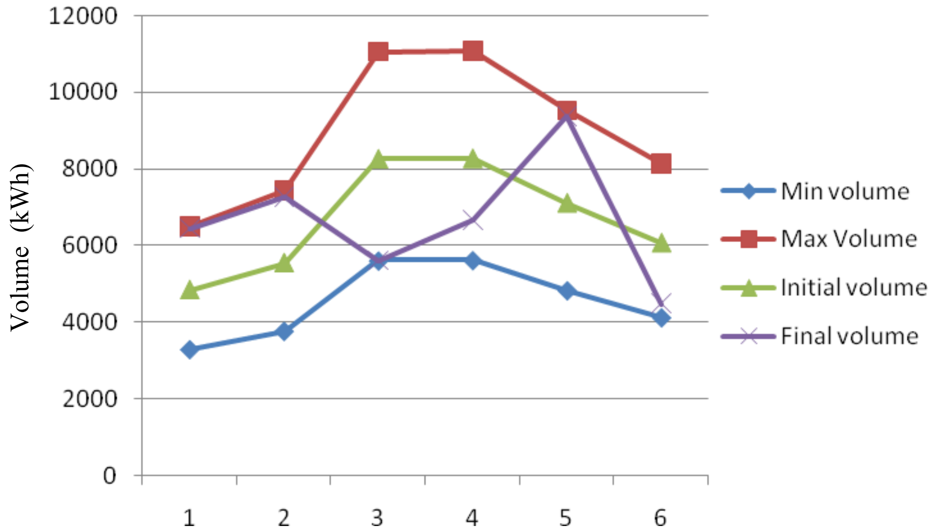

Fig.5.2. Variation of volume during the negotiation process

From fig 5.2., it is evident that the buyer agent transferred the quantities of energy from the periods of greater importance notably period 3, 4,6 to the periods during which seller agent cost are lower, i.e., periods 1,2 and 5. At 1, 2, and 5 the quantities transferred reached its maximum acceptable limit. Value of volume reached its minimum acceptable limit, during 3rd period where the price is higher. The simulation results proved the intelligent speculation that the behaviour of market participants is as expected in managing prices and volumes.

5.6.Conclusions:

A buyer motivated negotiation strategy based on the demand response(DR) activities is developed for the negotiation process during bilateral contract. This strategy consists of two parts, namely seller strategy/price management strategy and buyer strategy/volume management strategy. Furthermore, the simulation results demonstrate that the behaviour of agents is as expected in managing energy volumes and prices. Hence this simulation tool can be considered as a decision supporting tool to assist the market players during the negotiation process of bilateral contracts in competitive electricity market.

Demand response management is the new concept in power industry. Since the negotiation strategies adopted in financial markets are not as such appropriate in electricity market, a simple strategy based on DR management is developed. The proposed Buyer Motivated Negotiation strategy consists of a seller strategy and a buyer strategy. This is another contribution of this research work from this chapter.

Chapter 6
Design of Hybrid Genetic Particle Swarm Optimisation (GPSO) for Uplift Forecast in Profit Ceiling Model(PCM)

6.1. Introduction

Most of the power sector reforms initially focus on the introduction of competition in generation and supply and defining new price mechanisms. Transmission and distribution areas are less affected due to their natural monopoly characteristics. Traditionally, the need of regulation is justified on the grounds of natural monopoly characteristics of public interested industries [102]. The principal mode of this regulation can be treated as a form of public regulation. Hence regulation can be viewed as a necessary but transitory arrangement until the introduction of effective deregulation involving private firms [103].

The term deregulation frequently refers to the practice of establishing competition in various sectors of power industry. Or in other words, this can be deduced as the exclusion of regulations laid down by the government agencies [104]. Conversely, for the growth of healthy electricity market or the introduction of a healthy competition needs the execution of a set of regulations. The phrase regulation is normally referred to monopoly markets. According to Oxford dictionary of economics: *"A rule individuals or firms are obliged to follow: or the procedure for deciding and enforcing such rules [...] These may be designed to promote public health andsafety [...] They may be designed to promote competition and prevent unfairtrading practices [...] In the last resort regulation relies on legal sanctions [...]"*.Hence, regulation is a set of rules enforced by an authority to ensure unfair practices.

In general, market regulation comprises of defining the rules of the game, imposing obligations and evaluating the performance. Such regulations are vital for electricity markets since electricity is physically different from all other commodities due to its non storable nature. Furthermore, a minimum level of regulation is essential for the healthy functioning of any market. From the literature, *rates of return* and *price cap* regulation represent the two basic regulatory schemes for controlling prices. The financial markets often cited in the literature are heavily regulated. Very few works have been reported regarding the electricity market regulations and most of the works are in the arena of regulating tariff fixation [105].

Tariff fixing is treated as the primary mechanism in electricity market economic regulation. It is generally accepted that regulation is only a second best alternative. However, if the electricity market can be considered as a financial market and it cannot mimic market signals, regulation is the best. In this regard, the markets become efficiency oriented, rewarding efficient agents and penalizing inefficient ones. The cost of service approach in tariff regulation should be changed into a performance based approach which incentivizes efficient suppliers. Hence markets provide elbow room to suppliers to manage their affairs without interfering the Price or Revenue Cap approach to tariff setting. The Price Cap approach was a subsequent development which attempted to mirror the free play of the market. The Retail Price Index (RPI) approach is another regulatory model developed for electricity market. The regulatory models developed in recent years, the Rate of Return (ROR) and RPI-X are suitable for developed energy markets [106]. In this chapter, the scope of Profit Ceiling Model (PCM), the most recent evolution in this trend is evaluated for developing countries like India.

The major concern associated with the PCM is uplift forecasting for determining the quantitative relation between electricity price and uplift [107]. The uplift forecast can be treated as an optimization problem where the objective function is to maximize the allowed uplift for next year. The constraint for the optimization problem is chosen as the increase or decrease in average electricity price should be within a permissible range. Generally, game theory or random production simulation are used to solve these types of optimization problems. However, these techniques which require more hypothesis and assumptions are not highly appropriate for this particular application. The search algorithms for optimization problems, such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO) etc. are based on population evaluation, stochastic competition and cooperation [108,109]. These are found to be very effective in solving practical complex problems. In this chapter, a new approach termed as Hybrid Genetic Particle Swarm Optimization (GPSO) is used to solve the optimization problem for forecasting the uplift for the next year. The proposed GPSO approach is found to be very effective in terms of computational complexity and optimization. Hybrid GPSO combines the merits of GA and PSO, i.e., the uniqueness of PSO is its faster convergence towards global optima in the early stage of search and the performance of GA may augment near global optima.

This chapter is organized as follows: the two well developed models(ROR model and RPI-X) and the recent PCM are compared and contrasted in section 6.2, the regulation aspects on project investment is analyzed in Section6.3, section 6.4 dealt with the regulation of electricity price level especially uplift forecasting using GPSO, the ways by which PCM regulation enhances competition by providing incentives to aged and new plants are described in section 6.5 and finally Conclusion in section 6.6.

6.2.Regulation Model Selection:

Regulation model selection for electricity price is the major issue concerned with electricity market model. The two typical regulation models generally used across the world are the Rate of Return (ROR) model of the United States and the Retail Price Index (RPI-X) model of Britain [110]. Different countries have different goals, thus their selection criterions of regulation model are different. The purpose of this chapter is to analyze an electricity market regulation model which is applicable to developing countries specifically India.

6.2.1.Analysis of the two existing models

The first regulation model namely the Rate of Return (ROR) model, originated from United States electricity reform is widely used in many countries. The ROR model can be mathematically expressed as:

$$R(p,q) = C + S(RB) \tag{6.1}$$

where R is the income function of enterprise which depends on the price p and quantity q, C is the cost (e.g. fuel cost, salary, tax and depreciation etc.), S is the rate of return set by government and RB is the reasonable return base which is the total capital investment of enterprise.

The power industry reforms in Britain gave birth to another model namely, the Retail Price Index (RPI-X) model. RPI or Retail Price Index indicates the rate of inflation. X is the growth rate of production efficiency in a period of time. In fact, The Retail Price Index model is based on the weighted average price of products or services. Here, effective generation output is considered as the weight, and hence calculates the weighted average electricity price [105].

The model is as follows:

$$\begin{aligned} P_{t+1} &\le P_t\left(1 + RPI - X\right) \\ P_{t+1} &= \sum_k w_k p_k \end{aligned} \tag{6.2}$$

where P_{t+1}, P_t are the weighted average electricity price, whose period of time are t+1 and t respectively, w_k and p_k are effective production and price of product k.

The Rate of Return (ROR) model supports investment from producers/enterprisers without appreciating them through incentives. The major reasons for this lack of appreciation are: there is no incentive mechanism for efficiency improvement since the rate of return is always fixed after bargaining. The second one is the return base which is the capital invested by producers and hence it may lead to excess investment. The main peculiarity of the RPI-X model is that it gives separate incentives for producers, but it may pin down the investment from entrepreneurs. This refrainment of investors is due to the investment risks and the increase in price range, which is often limited by exogenous variables. On the other hand, the investment risks are to be assumed by customers /consumers in ROR model. Therefore, the zest for investment of producers is more in ROR model [104], [111].

Even though these two models are entirely differed on incentives and investment attraction, in practice there are some similarities exist between these two models [104]. While determining the price level in RPI-X model, the regulators have to consider the actual cost and return of enterpriser's investment over a period of time. In the second case, if the regulators are ignorant about the total cost of producers, their aim is to balance between incentives and profits [104]. Hence RPI-X model can be treated as a ROR model with affixed regulation period [106]. From the analysis of these two models, it can be inferred that Rate of Return (Finance evaluation) is the basis of any regulation aspects.

6.2.2.Overview and analysis of Profit Ceiling Model suitable for developing countries:

RPI-X model is suitable for countries like Britain, where the electric power industry is almost saturated. In Britain, the generation reserve percentage increased to 30% and load growth rate decreased to less than 1%, and no more newly-built capacity is encouraged [112]. However, RPI-X model is not appropriate for power Industries in developing countries because of the following reasons. Firstly, the model will restrain investment on generation capacity, which is not preferable for the healthy development of electric power industry. Secondly, electricity price in developing countries often fluctuates to great amplitude. Thirdly, it is hard to determine X, namely the increase percentage of electric power production efficiency. Lastly, negotiations may waste time and there are situations where authorities are breed corrupted. On the other hand, ROR model is a financial evaluation method. The only concern with ROR model is the lack of competitive mechanism.

The Profit Ceiling Model (PCM) is a modification of ROR model. The PCM can be basically treated as a price ceiling method. However, it can be generalized as a price regulation model like ROR and RPI-X. The PCM is mathematically defined as

$$P_{\max} = \overline{C_a} + C_s\left(A_{m+1}\right) + uplift\left(P_{av}\right) \tag{6.3}$$

where $P_{\max}$ is the price limit of regulation, C_a is the average social active cost, $C_s(A_{m+1})$ is sunk cost which takes the expected profit A_{m+1} as variable, $uplift(P_{av})$ is uplift space which takes average electricity price P_{av} as variable.

The PCM regulation should match with the national guidance policy of electric industry in each country. In the policy of reforming the RPI Pricing, which is generally approved by almost all developing countries, there are some specific requirements [110], [111]. Firstly, generation price must be classified according to social average cost. Secondly, generation price must be rechecked and revised according to RPI Pricing. The expected profit of the whole operation period will determine the sunk cost $C_s(A_{m+1})$. Lastly; the electricity price must be kept in a smooth level. $uplift(P_{av})$ is the control variable of average price.

The PCM regulation incorporates the soul of the two typical regulation models. The PCM integrates the concept of RPI i.e., the active cost with real price of materials and service, and decouples the sunk cost with price index. The PCM adopts the financial tool of ROR, i.e., the expected profit in operation period is revised automatically. At the same time, the PCM conquers the shortcomings of ROR model. On the one hand, the PCM encourages the competitive mechanism in project investment (e.g. public bidding for exploitation right [113]). Hence, by adopting the PCM the regulatory authority may control the project cost within the specified limits. In PCM, the price is considered to be within a range rather than a constant value. In this manner, the PCM can control excess investment in initial stage as well as augment incentives in the operating period. Or in other words, PCM regulation can be divided into two parts, Regulation on investments and regulation on incentives.

6.3.Regulation aspects on Project Investment:

In the mathematical expression for PCM regulation (3), the sunk cost $C_s(A_{m+1})$ is significant to the initial investment. The determination of $C_s(A_{m+1})$ is related to the initial investment (I), expected internal rate of return (i), and the operation period (n). These parameters are derived from the market competition mechanism, not by any guidance of government planning. Hence, the investment regulation is really significant in electricity market. Investment regulation can be divided into two parts: first introduction of competitive mechanism in initial investment like incorporation of public bidding and the second one is to collect the basic information for investment regulation such as internal rate of return, investment required per unit megawatt etc. At present, power industry in almost all developing countries is still in the infant stage of attracting investment. Hence, the reasonable construction cost of power plants has to be assured. However, the excess investment must be removed. At this stage, the regulation authority should refer to the developed electricity markets to augment the competition on generation investment. The induction of public bidding in generation investment may break the government monotony, and enhance the competition for generation ownership. The PCM provides a competition mechanism for project investment as follows [107].

Suppose a new power plant with capacity S MW, is to be built in a certain place and the expected annual utilization hour be T and operation period be n years. Regulatory authority invites bidders for generation ownership. Let j investors participated in the bidding process. The major bidding parameters are (i) Dynamic total investment - K_j (ii) capital proportion - f_j (iii)capital return rate - ROR_j (iv) loan interest rate- γ_j (v)loan term- τ_j .Then the annual worthy recovery for loan and capital are respectively A_l and A_c

$$\begin{aligned} A_l &= K.(1-f).crf(\gamma,\tau) \\ A_c &= K.f.crf(ROR,n) \end{aligned} \tag{6.4}$$

where *crf* is the capital recovery factor.

Subsequently, the equivalent return rate i of dynamic total investment can be obtained by solving the equation below

$$K-\sum_{t=1}^{\tau} A_l \frac{1}{(1+i)^t} - \sum_{t=1}^{\tau} A_c \frac{1}{(1+i)^t} = 0 \tag{6.5}$$

Then the annual recovery A can be calculated as

$$A = K.crf(i,n) \tag{6.6}$$

Consider the example, for a certain investor the bidding parameters are; dynamic total investment be 100 million INR, capital proportion be 20%, loan interest rate be 8%, loan term be 10 years and capital return rate be 12%.

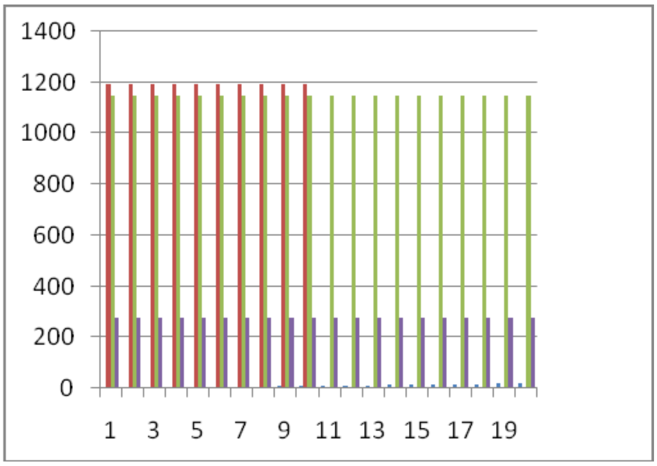

Fig.6.1.Computation of the annual worth recovery in power plant life cycle

From the fig.6.1, it is evident that the annual worthy recovery for loan A_l is 11.922 million INR, the annual worthy recovery for capital A_c is 2.678 million INR, the equivalent return rate i of dynamic total investment is 9.2%, and the annual worthy recovery A is 11.1 million INR.

Let the bidder V has the minimum annual worthy recovery. Then the dynamic total investment K_v and return rate i_v of bidder V are treated as the initial investment K and equivalent return rate i of the power plant respectively. To guarantee the quality of construction, the dynamic total investment K is revised by the regulating authority as

$$K_{reg} = \frac{S}{S'} K \tag{6.7}$$

If the bidders bid with different type power plants, the active and sunk costs must be considered simultaneously. The initial investments of power plants can be determined with public bidding. Bidding is basically a competition balancing procedure. This balancing process should consider the market risks associated with the investors. Hence bidding is a process which gathers information and that information may act as the foundation for the decision making of regulatory authority.

6.4.Electricity Price Level regulation:

The second major objective of electricity market regulation is to stabilize the electricity price fluctuations. In a competitive power market, price fluctuations are common. Hence, control measures must be taken to diminish these fluctuations. From the historical analysis of electricity markets across the globe, it is evident that price cap alone could not effectively confine price fluctuations. However, PCM incorporates price ceiling with dynamic adjusting mechanism. This dynamic adjusting mechanism is solely based on the uplift controlling of electricity price level.

6.4.1.Uplift Controlling of Electricity Price level:

The electricity price level is generally influenced by the uplift. To deduce the quantitative relation between uplift and electricity price level, initially the regulatory authority may induce a functional relationship. A statistical curve $P = p(q)$ of data taken from Indian Electricity Market is shown in fig.6.2.

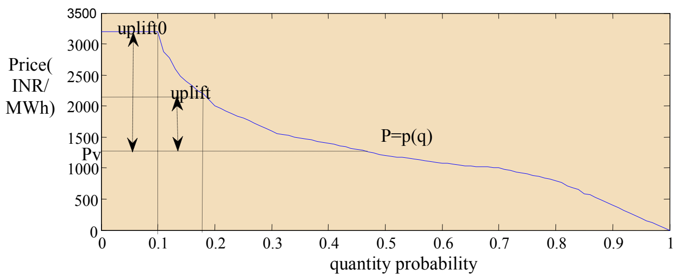

Fig.6.2.Statistical curve of data taken from Indian Electricity Market

Different types of fuels (difference in active cost C_a) and various loan repayments (difference in sunk cost C_s) will lead to different embedded cost $C_a + C_s$ of power plants. At peak loads, the power plants will operate in such a way to attain maximum effective capacity. Therefore the weighted average price of the embedded cost [107] is given by,

$$P_b = \sum_i \beta_i \left(C_{a_i} + C_{s_i}\right) \tag{6.8}$$

where $\beta_i, C_{a_i}, C_{s_i}$ are the effective capacity, active cost and sunk cost of power plant i respectively.
From the basics of economics theory specifically demand-supply relation, the average electricity price P_{av} is a function of uplift, given by

$$P_{av} = f\left(uplift\right) \tag{6.9}$$

From fig.6.2, when $uplift = uplift_0$, the initial value of average electricity price can be obtained as

$$P_{av_0} = \int_0^1 p(q)dq = \int_{q_0}^1 p(q)\,dq + \left(P_b + uplift_0\right)q_0 \tag{6.10}$$

where P_b the weighted average is embedded cost in peak load.

From the inverse statistical curve and under the assumption that $uplift$ fluctuates around the point $uplift_0$, the quantity probability can be calculated as

$$q = \begin{cases} p^{-1}\left(p_b + uplift\right) & ;0 \le uplift < uplift_0 \\ q_0 & ;uplift \ge uplift_0 \end{cases} \tag{6.11}$$

Now, the average electricity price P_{av} is given by

$$P_{av} = f\left(uplift\right) = \int_q^1 p\left(q\right)dq + \left(P_b + uplift\right)q \tag{6.12}$$

From the analysis of quantitative relation between uplift and average price, it is evident that the method is quite simple and feasible but very much depend on the uplift forecast.

6.5.Design of GPSO for Uplift Forecast:

To regularize the electricity price range in an electricity market, it is necessary for the regulatory authority to forecast the uplift for the next year. The uplift forecast is merely an optimization problem where the objective function is to maximize the allowed uplift of the next year subjected to the constraints on average electricity price level. The optimization problem can be formulated as,

$$\begin{aligned} \max \quad & uplift = f^{-1}\left(P_{av}\right) \\ s.t. \quad & P_{av} \le P_{av}\left(1 + x\%\right) \end{aligned} \tag{6.13}$$

where the variables are x - the growth rate of P_{av} and f the shape of statistical curve.

X is affected by the socio economic factors and hence can be determined by the regulatory authority. Even though the shapes of curves of series years are almost similar in stable market, the determination of shape of curve f is too difficult in developing countries where the market is highly unstable.

The classical optimization methods and game theory are not suitable to solve this optimization problem. While comparing the performance of GA and PSO, GA is very much responsive to the initial population. This dependence on the performance of GA to initial population is due to the arbitrary nature of the GA operators. Hence, the performance of GA may augment and the solution will converge to global optima, if and only if the initial population is well selected. Conversely, PSO is not as susceptible to initial population as GA. Moreover, in the early stage of search PSO may converge towards global optima at a faster rate and the uniqueness of PSO is its slow convergence near global optima [108]. Hence, a hybrid Genetic Particle Swarm Optimization (GPSO), which combines the merits of GA and PSO is proposed to solve this one.

6.5.1.Basics of Genetic Algorithm

GA explores the problem search space by simulating the evolution of a population of parameters as it goes from generation to generation. Based on the mechanism of natural selection or the Darwinian principle for biological reproduction and mutation i.e., survival-of-the-fittest, GA has emerged as a useful searching method in recent years. This searching method has been proved to be particularly effective in searching through poorly known solution spaces. Starting with an initial set of random solutions called population; GA generates a sequence of populations by using a selection mechanism, mainly crossover and mutation. Each individual in the population is called a chromosome and each chromosome comprises a string of individual structure called genes. During each generation, the chromosomes are evaluated, using some measure of fitness which reflects the evaluated performance index, and the new chromosomes, called offspring, are obtained by either merging two chromosomes from current generation using a crossover operator or modifying a chromosome using a mutation operator. A new generation is then formed by selecting some of the parents and offspring and rejecting others, according to their fitness values, and population size is generally kept constant. Therefore, the most suited individuals are likely to survive and generate offspring for improving the performances.

6.5.2.Basics of Particle Swarm Optimization:

Like GA, PSO is initialized with a population of random solutions. Its development was based on observations of the social behavior of animals such as bird flocking, fish schooling, and swarm theory. As described by Eberhart and Kennedy, the PSO algorithm is an adaptive algorithm based on a social-psychological metaphor; a population of individuals (referred to as particles) adapts by returning stochastically toward previously successful regions. During each generation, each particle is accelerated toward the particle’s previous best position and the global best position. New velocity value for each particle is calculated based on its current velocity, the distance from its previous best position, and the distance from the global best position. This new velocity value is then used to compute the next position of the particle in the search space. This process is continued until a minimum error is achieved.

6.5.3.Hybrid GPSO:

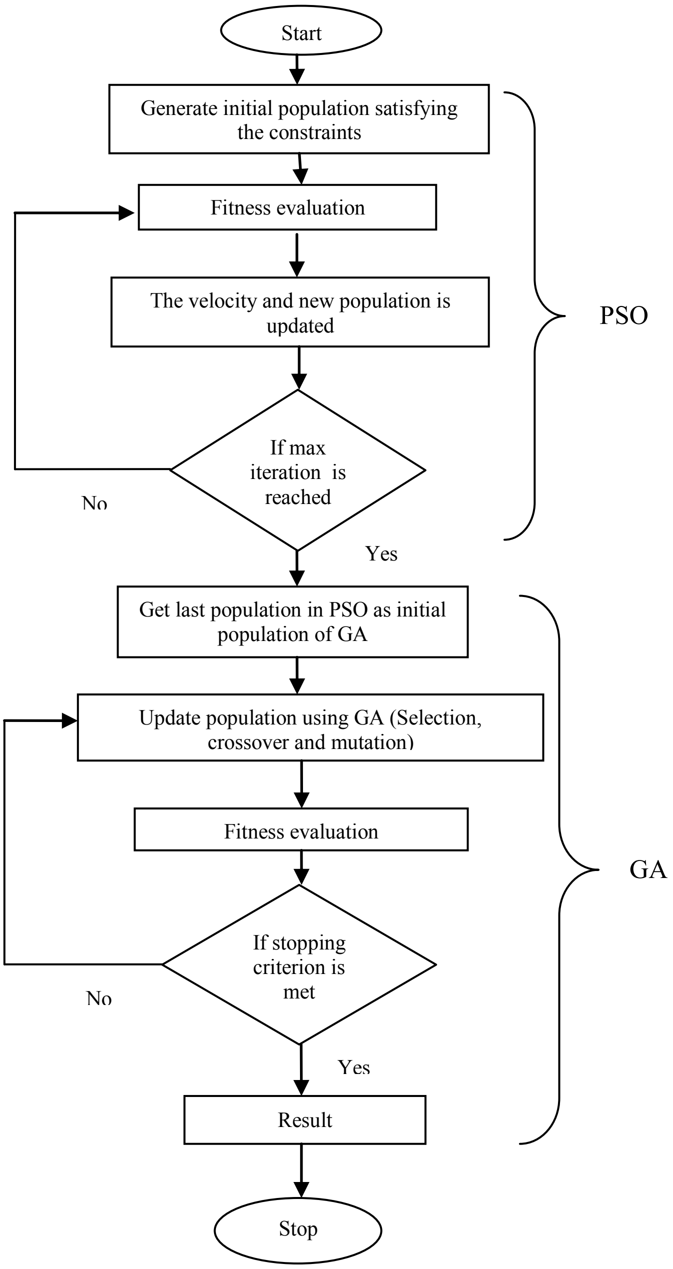

Fig.6.3. Steps involved in GPSO

In the first stage of optimization, an initial population is created satisfying all the constraints. According to PSO algorithm, each member in the population move towards its best position as well as the global best position by updating its velocity and position. "The PSO algorithm for velocity and position updating is given by,

$$v_{id}(t+1)=v_{id}(t)+C_1*rand*\left[p_{id}(t)-x_{id}(t)\right]+C_2*rand*\left[p_{gd}(t)-x_{gd}(t)\right]$$

$$x_{id}(t+1)=x_{id}(t)+v_{id}(t+1);1\leq i\leq n,1\leq d\leq D \tag{6.14}$$

where C_1 , C_2 are the acceleration constants with positive values; $rand$ is a random number between 0 and 1".This process is continued until the maximum iteration or minimum error is achieved.

In the second stage of optimization, the algorithm switches to GA and GA takes the final population from PSO as the initial population. Then, using crossover and mutation new generations are created until the minimum error is achieved and hence solved the optimization problem [114,115]. The step by step procedure of hybrid GPSO algorithm is shown as a flowchart in Fig.6.3.

To check the viability of the proposed scheme, the uplift forecasting for the Indian Electricity market is carried out in MATLAB environment. The forecasts are evaluated using standard performance criteria such as Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Bias and Variance Proportions and Theil inequality coefficient.

The performance in forecasting the uplift for Indian electricity market during 2014 (using 2009-2013 historical data) by different optimization techniques are tabulated in table 6.1.

Optimization techniques	PSO	GA	GPSO
RMSE	3450	3210	620
MAE	759	832	231
MAPE	6.542	7.258	3.951
Variance proportion	0.062	0.059	0.032
Bias Proportion	0.0054	0.0049	0.0037
Theil Inequality	0.0428	0.0437	0.0352

Table 6.1.Comparison of optimization Methods in Uplift Forecasting

MAE and RMSE depend on the scale of variable, while MAPE and Theil inequality are insensitive to the scale of variable. The errors are tabulated in table 6.1. Forecasting performance is better for GPSO, whose error is smaller. From the results it is evident that the GPSO is a good candidate for the prediction of uplift in a highly unstable electricity market. The major advantage of this model is that the computation complexity and hence computational time is less and its adaptability is very strong.

6.6.Incentives for Aged and New Power plants:

Any regulation model is not completed without giving emphasis on incentive regulation. While considering the profit space theory in the incentive aspects, the power plants may be classified into (i) aged and new ones based on whether the investment is totally returned or not (ii) construction period, operation period and extension period depending on the power plant life cycle[116].The life cycle of power plant with different incentive mechanisms is as shown in fig.6.4.

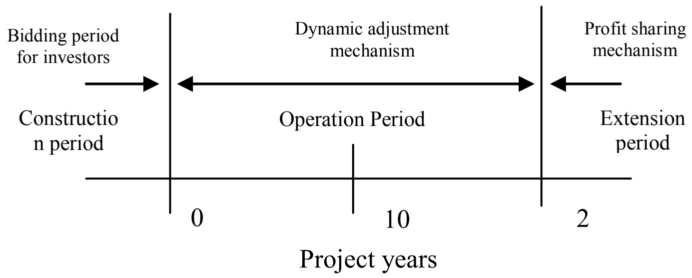

Fig.6.4.Incentive mechanisms during the power plant life cycle

6.6.1.Incentives for New Power Plants:

The power plant for which the investment is not totally returned is termed as new power plant. The PCM regulation incorporates a dynamic adjustment mechanism. According to this dynamic adjustment process, the expected profit of the following year is dynamically adjusted based on the actual profit of previous years. In addition to this optimal profit, the investors have a tendency to withdraw the investment as early as possible to reduce the effect of market risk [117]. According to PCM regulation, there are so many methods to reduce the investment returning period P_t. One method is bidders may adopt strategic bidding, i.e., increasing bid price to get extra profit in advance and hence reduce the investment returning period. Hence, the objective of the regulatory authority can be defined as an optimization problem defined as,

$$\begin{aligned} &\min \quad P_t \\ &s.t \quad K-\sum_{t=1}^{P_t}\left[R_t-(C_a-C_T)E_t-T_t\right]\frac{1}{(1+i)^t} \end{aligned} \tag{6.15}$$

where R_t is the actual income of the t[th] year , C_a, C_T are the active cost and per unit electricity tax respectively and $E_{t,}T_t$ are the actual generation quantity and tax of the t[th] year.

6.6.2.Incentives for Aged Power Plants:

Generally Power plants in developing countries get equal fixed electricity price irrespective of load(peak or valley load does not affect the electricity price). This mechanism is not scientific while looking from the incentive aspects. The consequence is at the time of valley load all generators will try to deliver as much contract quantity as possible and that may lead to problems with grid dispatching [110]. This situation may destroy the optimal resources allocation of market mechanism.

Hence, PCM incorporates Profit sharing mechanism which is widely accepted in modern incentive theory. According to profit sharing mechanism, the aged power plants are not fixed priced rather they are priced based on market competition. Moreover, the profit above is shared between power Grid Company and Generation Company. In fact, the grid company share is generally returned to customers so as to decrease average electricity price or kept as fund for grid improvements.

6.7. Conclusions:

One of the major concerns during electricity market reform is the selection of a particular regulation model. After evaluating two already existing models, this work suggests the Profit Ceiling Model (PCM) for electricity markets in developing countries. PCM regulation model incorporates the regulation aspects for investors and regulation on electricity price level. To regulate the electricity price level, the quantitative relation between average electricity price level and uplift is analyzed and it is inferred that the major concern with the regulation of electricity price is the uplift forecasting. Simulation results on the uplift forecasting of Indian Electricity market for the year 2014 demonstrate that Hybrid Genetic Particle Swarm optimization (GPSO) method is a best candidate for this optimization problem. Moreover, PCM introduces incentive mechanisms to reduce excess investment in new plants and dynamic adjusting mechanism to remove extra profits in aged plants. Considering all these aspects, the PCM can be treated as a best model applicable to electricity markets in developing countries especially to Indian electricity market.

The latest development in financial economics is Profit Ceiling Model (PCM). Many commodity markets adopted this model to incorporate incentive mechanism, profit sharing mechanism and to attract investment by reducing the risks faced by investors. The scope of PCM in regulating electricity market of developing countries is analyzed in this work. The major problem associated with PCM is the uplift forecast which can be treated as an optimization problem. Since the electricity market prices are highly fluctuating especially in developing countries, it is very difficult to solve this optimization problem using classical optimization solutions. Hence, a hybrid GPSO, which combines the merits of GA and PSO, is proposed to solve this optimization problem. The major contribution of this chapter is the design of Hybrid GPSO to solve an optimization problem.

Chapter 7
Design of a Hybrid Genetic Particle Swarm Tuned Sliding Mode Controller for Electricity Market Bidding Dynaimcs

7.1.Introduction:

Power Bidding is emerged as one of the major problems in electricity market after the introduction of market oriented reforms in the electric Power industry. In a perfectly competitive market, power suppliers are not the price makers. From microeconomic theory, the optimal bidding strategy for a supplier is to bid marginal cost [118]. However, the generators bid other than the marginal cost with an intension to exploit the imperfections in the market and hence increase their profit. This bidding behavior is known as strategic behavior [119]. The stability of bidding dynamics is very important for reliable power supply [120]. Any instability in bidding dynamics can cause power shortage which may have resulted in huge economic and social losses [121]. In this context, it is highly essential to achieve the stability of bidding dynamics of power producers.

Theoretically, power bidding is a repeated oligopoly game [122]. Consequently, power producers may reach their equilibrium bidding strategy by continuously updating their bids [123]. Many researchers tried to model the bidding behaviors of power producers as various game models and the game equilibrium were treated as the optimal bidding strategies of power producers [124]. In the practical scenario, it is difficult for power producers to reach optimal bidding strategies due to their bounded rationality.

In recent years, many researchers endeavor to formulate electricity price equilibrium by dynamic adjustment of power producer bidding. Xiaojiano et.al. and Yuan et.al. presented Power bidding dynamics as a Cournot model with transmission constraints [125,126]. Xinhua et.al. discussed a delayed dynamic model for optimizing generating units' power output [127]. Though the model assures system stability it did not bring any additional revenue to the power producers. Zhang et.al. and Yang et.al. analyzed the duopoly Cournot Game model with transmission constraints and its stability [128,129]. The basic idea of the above literature is that the bidding strategy of every power producer is modeled with a dynamic adjustment process, and several dynamic adjustment processes are looked as a dynamic power bidding system, whose stability is analyzed with traditional dynamic system or differential equation method. However, these literatures focused on the general duopoly power producer's case, whereas triopoly or oligopoly case has hardly been studied. Zhang et.al. analyzed the bidding dynamics for a triopoly and tried to stabilize the chaos present in the bidding dynamics with a state delayed feedback control method[130]. Still this method is not suitable to maintain the equilibrium for best response or adaptive bidding dynamics. In this paper, the generator bidding problem in an oligopoly market is formulated as a control problem and the modeled dynamics shows a typical chaotic nature.

In the economic theory point of view, many methods and techniques have been developed to control the chaos [3]. They are mainly passive control [4], back stepping control and sliding mode control [6]. Among the different techniques mentioned above, the sliding mode control (SMC) can deal with the uncertainties/chaotic nature of the system. In SMC, the major issues are related with the design of sliding mode controller specifically the design of sliding surface. Once an appropriate sliding mode surface is designed, the controller can restrain the effect of chaotic nature of the system and has stronger robustness on the external force disturbances. However, design of the coefficients of the sliding surface for the present chaotic bidding dynamics mainly depends on the designer's experience. Hence, so far there is no systematic design procedure developed for the design of sliding surface coefficients. This may be overcome by adopting certain auto tuning techniques [132,133].

Auto tuning techniques, for the design of coefficients of the sliding surface, can be adopted from the search algorithms which are well established in the research arena of computational intelligence. These search algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO) etc. are based on population evaluation, stochastic competition and cooperation. These are found to be very effective in solving practical complex problems [134, 108]. A new approach termed as Hybrid Genetic Particle Swarm Optimization (GPSO) is used to tune the parameters of sliding surface parameters and found to be very effective in terms of computational complexity and optimization. Hybrid GPSO combines the merits of GA and PSO, i.e., the uniqueness of PSO is its faster convergence towards global optima in the early stage of search and the performance of GA may augment near global optima.

In the proposed approach to control the nonlinear chaotic bidding dynamics, initially the controller is designed using back stepping sliding mode idea. Then, the sliding surface parameters of the controller are tuned with hybrid GPSO. During the designing of the controller, the stability of the closed loop system as well as the dynamic characteristics of the system are considered to ensure the robustness. Simulated results are provided to reveal the efficacy of the proposed hybrid GPSO sliding mode controller for chaotic bidding dynamics for an oligopoly electricity market.

The structure of the chapter is organized as follows: the theory of bidding dynamics and its control system perspective is delineated in section 7.2., state space form for bidding in an oligopoly market is developed in Section 7.3, sliding mode control theory concepts and design of Switching Surface and Controller in section 7.4, description of Hybrid GPSO for tuning the sliding surface parameters in section 7.5, Simulation Results and Discussions in section 7.6 and finally Conclusion in section 7.7.

7.2.Theory of Bidding Dynamics:

In a real time electricity market, generators submit their bids to an Independent System Operator (ISO). After proper analysis of bids and power system network constraints, ISO determines the MCP (Market Clearing price) and hence clears the market [135]. During the process of market clearing, each individual generator will come to know about the publicized MCP and its scheduled generation [136]. In the next phase of bidding process, each generator will adjust its bid with an aim to maximize its profits [137]. In this regard, the dynamic bidding process may be modeled as a dynamic feedback system or as a control problem in which the output MCP is fed back to individual generators to adjust their bids [1].

From the basics of power system economics, let the cost function of power producer i is chosen as a quadratic function [119]

$$c_i\left(q_i\right) = \gamma_i q_i + 0.5 \, q_i^2 / \beta_i \tag{7.1}$$

where $i = 1,2,3,4$ with cost parameters $\alpha_i, \beta_i > 0$ and q_i is the power quantity produced by producer i. The bidding function is chosen as [119]

$$b_i\left(\alpha_i\right) = \alpha_i + q_i / \beta_i \tag{7.2}$$

which is parallel to its marginal cost curve and the power producer should achieve their marginal profit by adjusting the strategic bidding variable α_i.

Based on supply-demand theory in economics, the market clearing price p is given by [118],

$$p = \left[Q + \sum_{i=1}^{N} \alpha_i \beta_i\right] \Big/ \sum_{i=1}^{N} \beta_i \tag{7.3}$$

where Q is the power demand. Then, the equilibrium quantity of power producer i is given by [118],

$$q_i^* = \left[\left(Q + \sum_{i=1}^{N} \alpha_i \beta_i \right) \Big/ \sum_{i=1}^{N} \beta_i - \alpha_i \right] \beta_i \tag{7.4}$$

The profit function π_i of power producer is

$$\pi_i(\alpha_i) = \left[(p - \gamma_i)(p - \alpha_i) - 0.5(p - \alpha_i)^2 \right] \beta_i \tag{7.5}$$

The optimum value of strategic bidding variable is given by [137],

$$\alpha_i^* = \frac{\gamma_i \sum_{i=1}^{N} \beta_i}{\beta_i + \sum_{i=1}^{N} \beta_i} + \frac{\beta_i \left[Q + \sum_{j \neq i}^{N} \alpha_j \beta_j \right]}{\left(\sum_{i=1}^{n} \beta_i \right)^2 - \beta_i^2} \tag{7.6}$$

To adapt with the market dynamics fluctuations due to the bounded rationality of the electricity bidding market, the bidding strategy of the power producers should be adjusted based on the incomplete information available from the market [138]. Due to lack of global information of power market, each market participant decides its electric quantity according to the local estimate of its own marginal profit and adjusts its bidding following a bounded rationality dynamic adjustment process in order to obtain the high profit as far as possible.

Among the several bidding dynamic strategies developed for the power producers, two types of dynamics are considered for the analysis of the system [127,139].

In the first type, the power producer adjusts its bidding dynamics based on the marginal profit.

$$\alpha_i(t+1) = \alpha_i(t) + k_i \alpha_i(t) \frac{\partial \pi_i(\alpha_i, \alpha_j)}{\partial \alpha_i} \tag{7.7}$$

where k_i is the adjustment speed.

In the second type, which is also known as adaptive adjustment dynamics, the power producers adjust their strategy based on the linear combination between the last bidding strategy and the optimal bidding. The corresponding bidding dynamics is mathematically expressed as:

$$\alpha_i(t+1) = \theta_i \alpha_i(t) + (1 - \theta_i) \alpha_i^*(t) \tag{7.8}$$

Where $0 \le \theta_i \le 1$ the adaptive adjustment is factor and $\alpha_i^*(t)$ is the best response of power producer i

7.3.State Space Modeling of Bidding Dynamics:

An oligopoly market is a market dominated by fewer large firms i.e., more than 70% of market shared by four producers [140]. It is assumed that among the 4 power producers, two of them adopt bounded rational dynamics and the other two adopted adaptive adjustment dynamics, then the state space model of bidding dynamics with 4 producers are obtained from (7) and (8) as,

$$\left.\begin{aligned} \dot{x} &= -k_1 x[1-\delta_1]\beta_1\left[x - x_{opt}\right] \\ \dot{y} &= (1-\theta_1)\left[y - y_{opt}\right] \\ \dot{z} &= -k_2 x[1-\delta_2]\beta_2\left[z - z_{opt}\right] \\ \dot{w} &= (1-\theta_2)\left[w - w_{opt}\right] \end{aligned}\right\} \tag{7.9}$$

x, y, z, w are strategic bidding variables, k_1, k_2 are adjustment speeds, β_1, β_2 are cost parameters, $\delta_i = \dfrac{\beta_i^2}{\sum_i (\beta_i)^2}$, and θ_1, θ_2 are adaptive adjustment factors. The $x_{opt}, y_{opt}, z_{opt}$ and w_{opt} are the optimum values of the strategic variables of four producers. The system described in (7.9) has three equilibrium points which are unstable saddle points.

Using the transformation,

$$\left.\begin{aligned} X &= x - x_{opt} \\ Y &= y - y_{opt} \\ Z &= z - z_{opt} \\ W &= w - w_{opt} \end{aligned}\right\} \tag{7.10}$$

After certain rearrangements, the state space model of the system is given by,

$$\left.\begin{aligned} \dot{X} &= -k_1 X[1-\delta_1]\beta_1[X + a] + u(t) \\ \dot{Y} &= (\theta_1 - 1)Y \\ \dot{Z} &= -k_2 Z[1-\delta_2]\beta_2[Z + b] + v(t) \\ \dot{W} &= (\theta_2 - 1)W \end{aligned}\right\} \tag{7.11}$$

where $u(t)$ and $v(t)$ are external control inputs and $a = x_{opt}$ and $b = z_{opt}$.

To verify the occurrence of unstable saddle points in the original system, the phase space plot of (7.9) can be plotted as shown in fig.7.1.

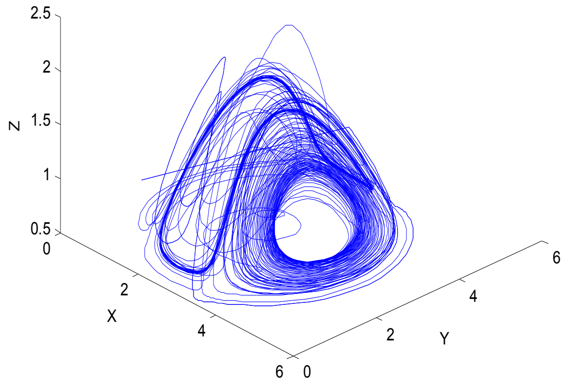

Fig.7.1.Phase portrait of bidding dynamics in an oligopoly market

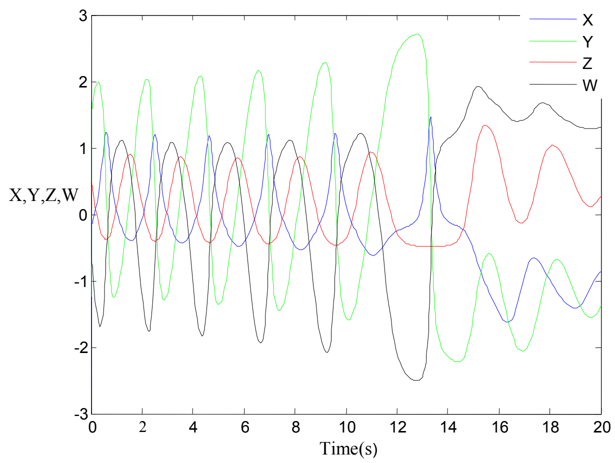

Fig.7.2.Variation of system states with time

The variation of system state trajectories with time is shown in Fig.7.2. From the above two figures it is evident that the bidding dynamics for the oligopoly market is a chaotic attractor or in other words the system under consideration is highly chaotic in nature. Hence, any small change in initial conditions brings unpredictable changes in its output. Therefore, a controller should be designed to stabilize the chaos present in system (7.9)

Since this nonlinear bidding model is not a strict feedback form, it may not possible to apply back stepping sliding mode control directly. Now, the system may be interpreted as a combination of two subsystems, which are of strict feedback form and as follows:

$$\left.\begin{aligned} \dot{X} &= -k_1 X\left[1-\delta_1\right]\beta_1\left[X+a\right]+u(t) \\ \dot{Y} &= \left(\theta_1 - 1\right)Y \end{aligned}\right\} \tag{7.12}$$

$$\left.\begin{aligned} \dot{Z} &= -k_2 Z\left[1-\delta_2\right]\beta_2\left[Z+b\right]+v(t) \\ \dot{W} &= \left(\theta_2-1\right)W \end{aligned}\right\} \tag{7.13}$$

The equations (7.12) and (7.13) represent subsystem (1) and (2) respectively. Since each subsystem is of strict feedback form, back stepping sliding mode technique can be applied to each subsystem.

7.4.Design And Stability Analysis Of Sliding Surface And Controller:

7.4.1.Overview of Sliding Mode Control Theory:

Sliding mode control (SMC) is a robust control method. SMC methods and techniques are developed and used effectively in industrial applications for the last three decades [72,141,142]. The major drawback of SMC is the unwanted chattering phenomena or the high frequency switching due to the discontinuous control actions. Many methods are proposed to reduce chattering such as using a continuous approximation of the discontinuous control, a combination of continuous and discontinuous sliding mode controllers, using the second or higher order sliding mode control (SOSMC,HOSMC) [143,144], and dynamic sliding mode control [145]. However, implementation of higher order sliding mode controller is difficult in practical applications [142,146]. On the other hand, some researchers addressed the chattering phenomena with the help of combined techniques, such as using SMC in conjunction with other methods such as back stepping.

Most control design approaches are based upon Lyapunov and linearization methods. However, in the Lyapunov approach, it is very difficult to find a Lyapunov function for designing a control and stabilizing the system. On the other hand, the linearization approach often yields to local stability. Among the Lyapunov approach methods, the back stepping approach presents a systematic method for designing a control law by proper selection of Lyapunov function [147], [148]. Hence, Back stepping technique guarantees global asymptotic stability [149].

SMC is a robust control method and back stepping can be considered to be a method of recursive control. The combination of these two methods, back stepping SMC, yields benefits from both approaches. The back stepping sliding mode control (BSMC) approach has been extended to some classes of nonlinear systems which need not be in the parametric pure feedback (PPF) form or parametric strict feedback (PSF) form [150]. By combining the sliding modes and the back stepping procedure, a robust controller can be designed to control the nonlinear systems with unmatched uncertainties since the stability analysis of sliding mode control fits very well within the recursive design.

In SMC, the state trajectory can be considered as a combination of two parts which represents two modes of the system. The first part, known as hitting/reaching phase consists of the state trajectory from initial condition to sliding surface. When the state trajectory hits the sliding surface, the controller pushes the trajectory along the surface to the equilibrium point, which is known as the sliding mode of the system.

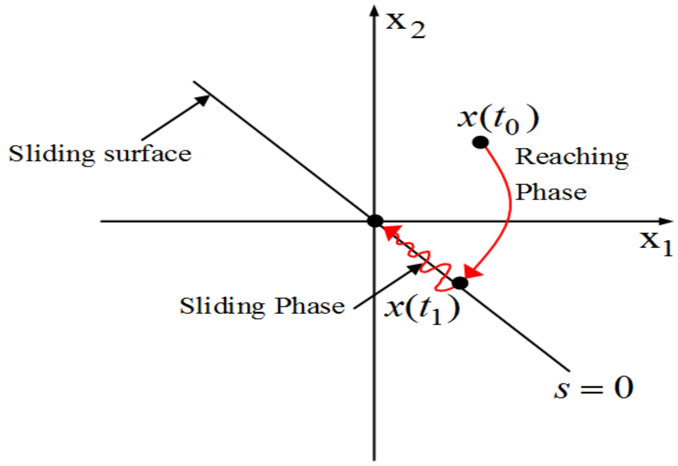

Fig.7.3.Sliding mode Concept

Therefore the sliding mode controller design includes a design of sliding surface and a proper control law. A suitable sliding surface ensures a stable system dynamics for the system under consideration and the control law guarantees a proper reaching condition and a stable sliding motion. The system shows fluctuations with parameter variations in reaching phase however it is insensitive to external disturbances and perturbations in sliding mode [151].

7.4.2.Design of Back Stepping Sliding Mode Controller:

In this section, for each of the two subsystems represented by (7.12) and (7.13), an asymptotically stable surface (σ) is defined as a function of the transformed states such that all system trajectories converge to the sliding surface in finite time and slide along the surface until they reach the equilibrium point(origin). The reaching conditions are normally established by defining the Lyapunov function and ensuring the stability in terms of Lyapunov stability conditions [152].

7.4.2.1.Sliding mode controller for Subsystem 1:

For the subsystem with transformed state variables X and Y, the sliding surface is chosen as $\sigma_1 = p_1 z_1 + z_2$ with $p_1 > 0$.

The variables z_1 and z_2 are defined as $z_1 = Y$ and $z_2 = X$

The Lyapunov function for subsystem 1 is chosen as follows ,

$$V_1 = \frac{1}{2} z_1{}^2 + \frac{1}{2} \sigma_1{}^2 \tag{7.14}$$

Then the derivative of V_1 can be derived as,

$$\begin{aligned} \dot{V}_1 &= z_1 \dot{z}_1 + \sigma_1 \dot{\sigma}_1 \\ &= (\theta_1 - 1) z_1^2 + \sigma_1 \left[p_1 (\theta_1 - 1) z_1 - k_1 \beta_1 z_2 (1 - \delta_1)(z_2 + a) + u(t) \right] \end{aligned} \tag{7.15}$$

So, the back stepping control law is designed as,

$$u(t) = -\left[p_1 (\theta_1 - 1) z_1 - k_1 \beta_1 z_2 (1 - \delta_1)(z_2 + a) + h_1 (\sigma_1 + \gamma_1 \operatorname{sgn}(\sigma_1)) \right] \tag{7.16}$$

where h_1 and γ_1 are positive constants. Substituting (7.16) in (7.15),

$$\dot{V}_1 = (\theta_1 - 1) z_1^2 - h_1 \sigma_1{}^2 - h_1 \gamma_1 |\sigma_1| \tag{7.17}$$

By choosing right values for constants h_1 and p_1, a positive definite matrix Q may be defined as

$$Q = \begin{bmatrix} 1 - \theta_1 h_1 p_1^2 & p_1 \\ p_1 & h_1 \end{bmatrix} \tag{7.18}$$

By choosing a vector, $z_A{}^T = [z_1 \quad z_2]$,

$$\begin{aligned} z_A{}^T Q z_A &= [z_1 \quad z_2] \begin{bmatrix} 1 - \theta_1 + h_1 p_1^2 & h_1 p_1 \\ h_1 p_1 & h_1 \end{bmatrix} \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} \\ &= (1 - \theta_1) z_1^2 + h_1 \sigma_1{}^2 \end{aligned} \tag{7.19}$$

Substituting the value of $(1 - \theta_1) z_1^2 + h_1 \sigma_1{}^2$ from (7.19) in (7.17),

$$\dot{V}_1 = -z_A{}^T Q z_A - h_1 \beta_1 |\sigma_1| \tag{7.20}$$

By choosing a positive definite Lyapunov function V_1 , $\dot{V}_1$ is obtained as negative definite. Moreover, $\lim_{t\to\infty} Y = 0$ and $\lim_{t\to\infty} X = 0$. Therefore, first subsystem when controlled by back stepping sliding mode controller is asymptotically stable.

7.4.2.2.Sliding mode controller for Subsystem 2:

For the subsystem with transformed state variables Z and W , consider the sliding surface as $\sigma_2 = p_2 z_3 + z_4$ with $p_2 > 0$. The variables z_3 and z_4 are defined as $z_3 = W$ and $z_4 = Z$.

The Lyapunov function for subsystem 2 is chosen as follows,

$$V_2 = \frac{1}{2} z_3{}^2 + \frac{1}{2} \sigma_2{}^2 \tag{7.21}$$

Then the derivative of V_2 can be derived as,

$$\dot{V}_2 = z_3 \dot{z}_3 + \sigma_2 \dot{\sigma}_2 \quad = (\theta_2 - 1) z_3^2 + \sigma_2 \left(p_2 (\theta_2 - 1) z_3 - k_2 \beta_2 z_4 (1 - \delta_2)(z_4 + b) + v(t) \right) \tag{7.22}$$

So, the back stepping control law is designed as,

$$v(t) = -\left[p_2 (\theta_2 - 1) z_3 - k_2 \beta_2 z_4 (1 - \delta_2)(z_4 + b) + h_2 \left(\sigma_2 + \gamma_2 \operatorname{sgn}(\sigma_2) \right) \right] \tag{7.23}$$

where h_2 and β_2 are positive constants. Substituting (7.23) in (7.22),

$$\dot{V}_2 = (\theta_2 - 1) z_3^2 - h_2 \sigma_2{}^2 - h_2 \gamma_2 |\sigma_2| \tag{7.24}$$

By choosing right values for constants h_2, c_2 and k_2 , a positive definite matrix P may be defined as

$$P = \begin{bmatrix} 1 - \theta_2 + h_2 p_2^2 & h_2 p_2 \\ h_2 p_2 & h_2 \end{bmatrix} \tag{7.25}$$

By choosing a vector $z_B{}^T = \begin{bmatrix} z_3 & z_4 \end{bmatrix}$,

$$\begin{aligned} z_B{}^T P z_B &= \begin{bmatrix} z_3 & z_4 \end{bmatrix} \begin{bmatrix} 1 - \theta_2 + h_2 p_2^2 & h_2 p_2 \\ h_2 p_2 & h_2 \end{bmatrix} \begin{bmatrix} z_3 \\ z_4 \end{bmatrix} \\ &= (1 - \theta_2) z_3^2 + h_2 \sigma_2{}^2 \end{aligned} \tag{7.26}$$

Substituting the value of $(1 - \theta_2) z_3^2 + h_2 \sigma_2^2$ from (7.26) in (7.24),

$$\dot{V}_2 = -z_B{}^T Q z_B - h_2 \beta_2 |\sigma_2| \tag{7.27}$$

By choosing a positive definite Lyapunov function V_2, $\dot{V}_2$ is obtained as negative definite. Moreover, $\lim_{t\to\infty} Z = 0$ and $\lim_{t\to\infty} W = 0$. Therefore, second subsystem when controlled by back stepping sliding mode controller is asymptotically stable.

From the above mathematical analysis, the stability of the proposed back stepping sliding mode control system can be guaranteed by choosing appropriate values for the switching/sliding surface parameters.

7.4.3.Hybrid GPSO for Tuning Sliding Surface Parameters:

Manual tuning becomes a difficult process due to the interaction between the control parameters of sliding mode controller. Over the past few years many methods were developed to tune controller parameters to optimum value to avoid manual tuning. Majorly accepted methods for auto tuning are Artificial Intelligence Techniques such as GA, PSO and hybrid GPSO which combines GA with PSO. This hybrid GPSO has an advantage over GA in terms of computational complexity and optimum value for controller parameters.

In GPSO, the optimization process consists of two phases. The first phase in which an initial population is generated which satisfies all the given constraints. Using PSO algorithm every single member in the population updates its own position and velocity while moving towards their best ever position. Thus, the population as a whole moves towards the global position. The second phase uses the GA algorithm. Here, the last population in PSO is taken as the first population for GA. Then new generations come into being using crossover and mutation until the minimum error criterion is achieved, thus solving the optimization problem.

The sliding surface parameters largely influence the closed loop performance of the sliding mode controller. Often their effect is non-intuitive which needs online tuning to achieve the best controller performance. Following the minimum error criterion in optimal control a general performance objective is made, i.e , the total deviation of the system states from the equilibrium point is taken as the fitness function which is to be minimized and is mathematically expressed as,

$$F = \sum_i X_i^{\;2} + Y_i^2 + Z_i^2 + W_i^2 \tag{7.28}$$

According to Lyapunov stability criterion, for the system to be asymptotically stable the matrices P and Q, whose elements are functions of sliding surface parameters, should be positive definite. In this context, the constraints for the optimization problem are as follow:

$$|Q| = \begin{vmatrix} 1-\theta_1 + h_1 p_1^2 & h_1 p_1 \\ h_1 p_1 & h_1 \end{vmatrix} > 0$$
$$|P| = \begin{vmatrix} 1-\theta_2 + h_2 p_2^2 & h_2 p_2 \\ h_2 p_2 & h_2 \end{vmatrix} > 0 \tag{7.29}$$

7.5.Simulation Results and Discussions:

For stabilizing the chaotic bidding dynamics, the controller should be selected depending on two aspects: the time taken by it to converge into a stable state should be less and the controller should not be complex but simple such that its practical implementation is easy and has a practical meaning.

Simulation studies were carried out in MATLAB environment to check out the viability of the proposed scheme in terms of reaching characteristics. To control the chaos during the chaotic bidding dynamics, the sliding mode controller has been designed with a different surface parameters viz. Untuned, GA tuned and hybrid GPSO tuned.

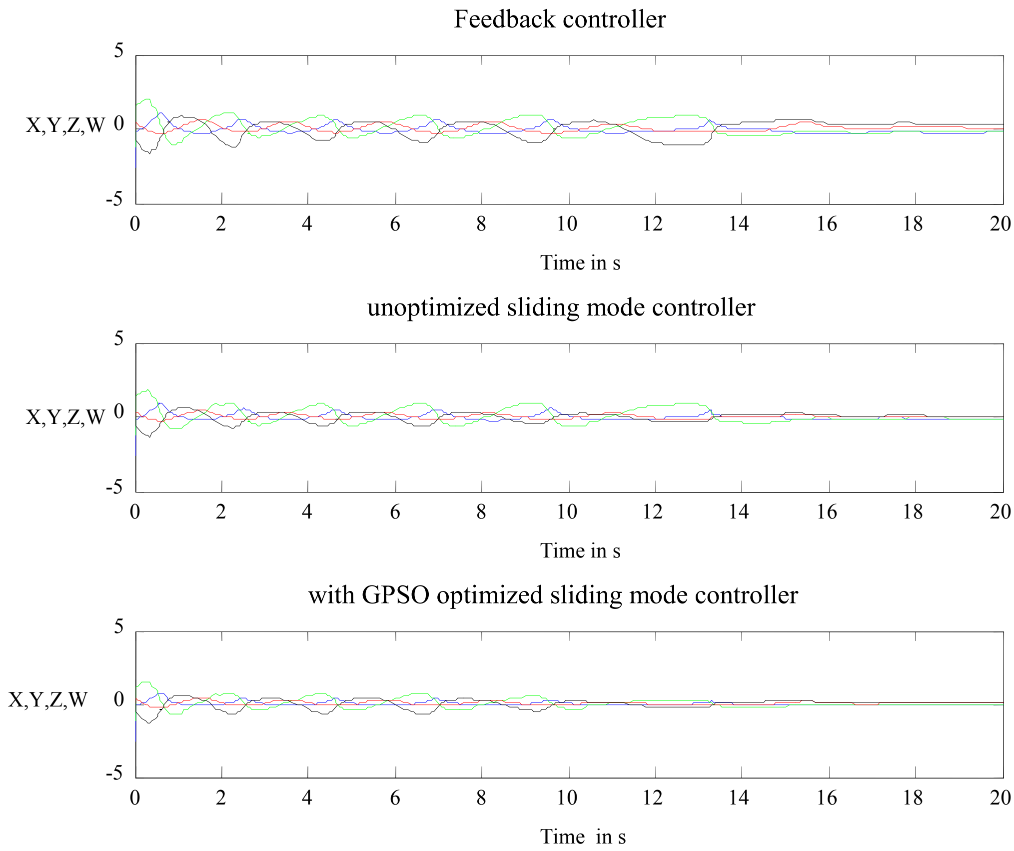

Fig.7.4.State trajectories of the system with different optimization techniques

The simulation results of the state trajectories for GA optimized, hybrid GPSO optimized and unoptimized sliding mode controllers are shown in fig.7.4. Undoubtedly, the proposed hybrid GPSO tuned sliding mode controller has a decreased settling time, over or/and under shoots and error when compared to other sliding mode controllers like GA optimized and an unoptimized sliding mode controllers.

The dynamics for the hybrid GPSO sliding mode controlled chaotic finance system is improved during the reaching phase. An account of the variations of all the parameters associated with the simulation results are shown in table 1. The tabulation statements strongly support the optimization procedure for the sliding surface parameters during the control process.

Properties		**Feedback Control**	**Unoptimized sliding mode control**	**Hybrid PSO-GA optimized sliding mode control**
Optimization stage		NA	NA	24.5234
Reaching phase characteristics	***Time taken to reach the equilibrium point with tolerance***	NA	in 19.542s	in 10.352s
	Mean square error	18.705	10.842	4.326
	Max overshoot/ undershoot	X-2. 5961 Y-1.9474 Z-0.9639 W-2.4869	X-1.8839 Y-1.7916 Z-0.8482 W-2.486	X-1.1931 Y-1.5579 Z-0.7229 W-2.1943

Table 7.1 Comparison of performance of various controllers in stabilizing the chaos in bidding dynamics

Producer	Unoptimized sliding mode controller				Hybrid GPSO Sliding Mode Controller			
	Bidding parameter	Dispatch	Profit	MCP	Bidding Parameter	Dispatch	Profit	MCP
1	0.0292	160	2616	16.35	0.0264	160	2618.1	16.363
2	0.1242	89.40	1641.7		0.105	105.83	1731.7	
3	0.2923	45.70	747.2		0.275	48.67	795.3	
4	0.0743	88.80	1451.9		0.0055	120.0	1963.6	

Table 7.2 Comparison result of bidding strategy and associated variables

The table indicates the comparison of bidding strategy and associated variables. From the table, it is evident that the profit of each producer is more in the case of Hybrid GPSO sliding mode controller than that of unoptimized sliding mode controller. The MCP for the simulated market with Hybrid GPSO is slightly higher than that of unoptimized sliding mode controlled electricity market.

The analysis of the proposed GPSO tuned sliding mode controller for the electricity market bidding in a practical situation shows that, any chaotic phenomenon that appears in a bidding dynamics because of the irregularity in electricity market can be controlled by altering the strategic bidding variable (state variable x) so that the whole bidding system could be brought back to a stable state. In case of a problematic situation most of the electricity market producers uses the method of altering the bids (changing the strategic variables). This method of controlling the chaos in dynamics by adjusting the bids is found to be very methodical in restoring the system. In the suggested system the numerical adaptations in the strategic variables rely only on the sliding surface parameters. Therefore once the sliding surface parameters are tuned correctly the implementation of the controller becomes a way lot simple.

7.6.Conclusions:

In this work, the hybrid Genetic Particle Swarm tuned sliding mode controller is fashioned in such a way, that it stabilizes the chaotic behavior of bidding dynamics for electricity market. The asymptotic stability of sliding surfaces is proven to be solid by Lyapunov stability theorem. The proposed sliding mode controller's potency and its adaptive abilities are validated by the numerical simulation results. It is found that, in the hybrid Genetic Particle Swarm (GPSO) sliding mode controller, the state trajectory reaches the equilibrium point at a faster rate than the Genetic Algorithm optimized and the unoptimized sliding mode controllers. Furthermore by using the hybrid GPSO approach to tune the sliding surface parameters the reaching phase dynamics can be notably improved.

Generally, the power bidding problems are addressed with game theory concepts. Due to the computational complexity associated with the discrete state concept, power bidding is viewed as a control problem. Even then, modern control techniques are never used to solve the bidding dynamics problem. However, the financial markets similar to electricity market which shows chaotic behviour is stabilized by using a sliding mode controller. In this context, the major difficulty is the design of sliding surface, specifically the tuning of sliding mode parameters. The major contributions in this chapter are threefold. These are (i) modeling of the power bidding dynamics of an oligopoly market with four producers in state space form;

(ii) design of a sliding mode controller to stabilize the chaos present in the bidding dynamics, and (iii) formulation of a hybrid GPSO algorithm to tune the sliding surface parameters of the controller. Thus, the design of a Hybrid GPSO tuned sliding mode Controller to stabilize the chaos in electricity market bidding dynamics is one of the major contribution of this research work.

Chapter 8
Modified Bidding Dynamics with Prosumer Concept

8.1.Introduction:

Electricity Markets around the globe are undergoing drastic changes to incorporate the latest technological developments and policy measures to counteract the climate changes specifically low carbon electricity [153]. Among these changes, one major change is the penetration of renewable energy systems such as solar photovoltaic systems, wind power generating systems, plug in electric vehicles. The stochastic character of the renewable energy brings the challenges to the independent system operator (ISO) and the market participants. From the independent system operator's point of view, the major challenge is to find a strategy to incentivize market participants to mobilize renewable energy generation. At the same time, the supply demand balancing even with the high penetrating renewable is a major concern of the ISO. On the other hand, the concern of market participants is how to achieve maximum profit with incomplete information about market rivalries and the uncertainty of the renewable energy generation. However, this new scenario may result in difficulty in load predictions due to the high-frequency changes in generation and loads. The demand side management is found to be a major solution to subside the high-frequency fluctuations and to balance supply and demand [154]. A modeling concept for a single building to participate in the market is developed in [155]. In this concept, the demand side units are grouped based on the flexibility of the units such as nonflexible loads, detachable generators and energy storages, and shiftable loads. Energy hub concept to handle multiple energy carriers is introduced in [156].

The aggregation of smaller consumers to form a prosumer concept is introduced in [157]. Many literatures focused on the optimal integration of local generation, flexible loads, storage devices are published recently [158,159]. In [160], it is empirically demonstrated that the bidding process with renewable integration outperforms the bidding process without renewable integration.

Generally, in a normal bidding procedure, the large consumers or distribution companies bid for the expected load irrespective of the price. Or in other words, in production side bidding the end use customers are not exposed to the time varying market clearing prices. Many research works are done in the production side bidding, while very few are in demand side bidding.

The bidding process for a retailer in Norwegian Electricity market is formulated in [161].Considering the uncertainty in prices, a linear bid curve for a single hour is developed and the load is considered as an inverse demand function. The model of an optimal bid for a large consumer with self-generation is developed in [162]. The economic benefits of agents with renewable such as solar photovoltaic and wind power generation are explored in [163]. Furthermore, in [164] decisions regarding the energy volume and delivery timing are optimized in the intraday market.

8.2. Integrating Renewable Sources into wholesale Electricity Market:

Integration of renewable sources to power system network may reduce the system costs especially the distribution side costs. Most of the renewable sources can address the problems faced at distribution levels such as congestion, inadequate transmission and related infrastructure, and losses. However, due to the peculiarity of these systems, the electricity market dynamics addresses new challenges. These challenges include:

1. *Effect of demand response actions in Electricity market dynamics*

Demand response actions affect the electricity market dynamics significantly such as an increase in the elasticity and economic efficiency of wholesale market operation. However, the majority of the electricity markets across the globe are still following the traditional concept of whole sale market and retail distribution. This concept should be revised to incorporate the demand response. For example, the electricity markets in the United States incorporate the new provisions to trade demand response parameters.

2. *Incorporating distributed generation.*

Exploitation of distributed generations, such as solar photovoltaic, combined heat and power, etc. influence wholesale market operation in exclusive ways. In Denmark, only combined heat and power plants can participate in wholesale power markets. However, solar photovoltaic systems are rarely participating in the whole sale markets. These solar systems affect the market operations indirectly by dipping the electricity demand during midday hours. From these observations, it is evident that a single approach is not appropriate to incorporate the distributed generation into the electricity market. As an alternative, a hybrid strategy with the coordination of centralized and distributed energy resources based on the localized peculiarities is to be developed. This problem is not addressed in this work and it remains as a future research area.

3. *Illustrating the role of storage devices*

Electricity storage either in mechanical, thermal, or chemical form is a promising area to simplify the concerns over the wind and solar systems impacts on market dynamics and to decrease curtailment. However, the limitation on proper policy and regulatory aspects regarding the role of storage devices are the major restriction on the participation of storage devices in the wholesale energy market. Promising solutions, such as allowing the owner of a storage resource to disaggregate these various services and sell them each to a third party for the transaction in markets, could induce more optimal use of storage options. This concern also may be addressed by a future research work.

8.3.The Concept of Prosumer:

Alvin Toffler, the author of the "The Third Wave"(1980) introduced the concept of a Prosumer and in literature the prosumer refers to the professional consumer. In the power system industry, the prosumer concept was introduced in [165]. Prosumer refers to an entity in the energy market who can act as a producer and consumer according to the market as well as self conditions.

Conventionally, small power system producers are defined as either small producers or small consumers of electricity. Recently, the latest technological developments in the arena of distributed generation/renewable sources allow even the end use consumers to produce and store energy. Thus, a new market entity, prosumer is emerged.

Generally, the prosumers are motivated economically and the major features are:

- Consumes, produces, and stores electricity and energy in general
- Optimizes the economic and to some extent the technological, environmental decisions regarding its energy utilization.
- Becomes actively involved in the value creating effort of an electricity or energy service of some kind

These features of a prosumer imply that an energy prosumer not only acts as a self sufficient end use customer but a consumer who is closely involved in the value chain of commercial energy suppliers also. The prosumer acts as a market player who is benefited by resonating with the supply demand relation and energy market dynamics. In turn, the prosumers can collectively enact in such a way to enforce the grid owners or energy market to resonate with the needs of consumers. The inception of Automatic metering services enable the prosumers the power to affect the market clearing prices and to negotiate to some extent [166].

The prosumer is a combination of physical components such as modern Smart Grid equipments, renewable energy sources, loads, and storage device. The major functions of a prosumer are energy consuming, producing or storing energy and participating in the market. The major challenge faced by prosumer is how to operate its physical components for its own benefit and to ensure reliable market operations.

8.4.Overview of Prosumer Oriented Electricity Market:

The establishment of a prosumer oriented energy market brings many benefits for end use customers and the society as a whole.

- On the consumption side, prosumers can reduce their energy use and or shift it over time in response to electricity prices.
- On the production side, the Smart Grid can widen prosumers' opportunities in the electricity market by supporting the connection and use of their privately owned Distributed Energy Resources (DERs). New players (Energy Saving Companies or ESCOs, Virtual Power Players (VPPs) and new devices (e.g. remote controllers) will give prosumers possibility to take advantage and make the profit of these options.

The main challenges for designing a wholesale market with prosumers are:

Minimizing Complexity: Most of the power markets across the globe are evolved into complex structure integrating the principles of economics and power system. Hence, while integrating the new concept of prosumer into a complex structure amplifies the complexity. This complexity reduces the enthusiasm of market players to participate in market dynamics and may induce unintended rivalries and conflicts.

Encouraging Investment: Generally, the energy prices depend only on the marginal cost of providing energy and are independent of the capital cost of producers. Since the penetration of prosumers into the market decreases the market clearing price, other market mechanisms such as bilateral contracts are getting more importance to adjust the returns of potential projects.

Harmonizing across timescales: Electricity market dynamics include short term price signals and long term price signals. A reliable market requires sensitivity to all the timescales. The major challenge in prosumer oriented is how to provide long-term market signals to encourage investments in prosumer's generation.

Ensuring Market Depth: In many power markets, a significant amount of energy is sold through bilateral contracts. It is observed that it reduces market participation. In bilateral contracts, the volume of energy is purchased months to years in advance. If the electricity market concerned is with significant bilateral contracts, it may leave a small day-ahead and real-time market for new, innovative, and flexible supply. Moreover, the spot-market prices might be inconsistent with marginal costs due to the limited supply of flexibility and the limited participation in the day-ahead and real-time markets. This decreases market efficiency by reducing the potential for market software to optimize supply resources based on their bid costs.

To overcome these challenges, the power system industry requires a transformation from a system built on a strict separation between wholesale and retail, or generation and distribution. This transformation can integrate these markets, such that assets from across the systems, can contribute to flexibility and reliability.

Moreover, market solutions are not the only option. Various hybrid designs like a combination of regulations and competitive markets can serve as an alternative. A key driver in any market or hybrid design is to start with the characteristics that maximize the value of the power system. This is to ensure the type and quantity of services, to check the feasibility of economic operation and to understand the design of the power system.

8.5.Mathematical Formulation of the Problem:

8.5.1.Market Policy:

According to the market policy adopted, the prosumer participates in the open electricity market generally via an agent. While the Prosumer buys/ sells active power to the grid, its aim is to minimize its cost or maximize its profit. The prosumers are charged for their active power consumption at the electricity market prices.

Demand Side Bidding:

The prosumer load can be classified into low priority and high priority loads. It is assumed that the prosumer places bids in two levels reflecting his priorities. It means the low priority loads can be served in periods of low prices and cannot be served at higher price periods. Two options can be considered at this level. These are shift option and curtailment option. In shift Option, Prosumers place two different bids for the supply of their high and low priority loads in the next operating periods. In curtailment option, Prosumers offer to shed low priority loads at fixed prices in the next operating periods.

8.5.2.Problem Statement:

The optimization function for each time block can be formulated as

$$Maximize(\mathrm{Re}venue - Expenses) = Maximize(\mathrm{Pr}ofit) \tag{8.1}$$

The prosumer sells the excess energy, if any, to the upstream network at the market price. If the power produced by the prosumer is not enough or too expensive to cover the local load, then power X is bought from the market at the same price.
The "Revenue" term is described in (8.1) is given by

$$\mathrm{Re}venue = AX + A\sum_i x_i \tag{8.2}$$

where A is the open market active power cost and x_i is the active power production of i th source of Prosumer. The term "Expenses" include costs for active power bought from the grid/electricity market. If Demand Side Bidding is considered, relevant costs are added to Expenses as shown in (8.2)

$$Expenses = \sum_i activebid\left(x_i\right) + AX + \sum_j loadbid\left(y_j\right) \tag{8.3}$$

Therefore the optimization problem can be rewritten as

$$Maximize(\mathrm{Pr}ofit) = Maximize\left(A\sum_i x_i - \sum_i activebid\left(x_i\right) - \sum_j loadbid\left(y_j\right)\right)$$

Subject to constraints,

$$X + \sum_i x_i + \sum_j y_j \geq P_{demand} \tag{8.4}$$

Where, P_{demand} is the demand of the prosumer at each time block and y_j is the active bid of j th load.

8.6.Simulation Results and Discussions:

For simplification, the prosumer bids are assumed to be linear and are given by,

$$activebid(x_i) = b_i x_i + c_i \tag{8.5}$$

where c_i is the hourly payback amount for the investment cost and b_i is the variable cost. The market dynamics simulated is with four producers and one prosumer where the producers bidding strategies are controlled by the Hybrid GPSO sliding mode controller described in the previous chapter and prosumer bidding is treated as an optimization problem.

At the same time it is assumed that the prosumer's profile consists of 4 solar PV systems of 2.5KW and 1 wind turbine of capacity 15 KW. The load profile of Prosumer varies from 5 KW to 50 KW with 4KW low priority loads.

The benefit of prosumer with two control options is tabulated in table 8.1.

Parameters	Unoptimized sliding mode controller	Hybrid GPSO sliding mode controller
Revenue(INR)	101.28	308.11
Load shed(kWh)	58	32
Load shed(as %)	21.53	34.73
Average Price(INR)	16.35	15.6

Table 8.1.Benefits of prosumer with different control options

From the analysis of the values tabulated, it is evident that the electricity costs are reduced for Hybrid GPSO sliding mode controller system. Even though the prosumer is feeding power to the grid at the grid price(reduced cost), the revenue is increased if the bidding dynamics is controlled by Hybrid GPSO sliding mode controller. Reduction in load shed with the introduction of renewable sources indicates that with the introduction of prosumer to the electricity market the service rendered during the hours of stress may be beneficial to other consumers too.

8.7.Conclusions:

The electricity market bidding dynamics developed in chapter 7 is modified with the concept of the prosumer. The prosumer oriented electricity market brings major benefits to both the end use customers and the society as a whole. The chapter also discusses the main challenges faced by the prosumer oriented electricity market. The economic evaluation of a particular prosumer in a real time market is done. Realistic values for the bids, actual market prices and typical load profiles and renewable productions are used for the simulations. Simulation results demonstrate that the Hybrid GPSO sliding mode controller is economically beneficial leading to either reduced energy prices for the consumers or increased revenues for the prosumer. Moreover, the service rendered during the hours of stress may be beneficial even for other customers.

Concept of prosumer is the latest development in power system industry. The prosumer oriented market is accepted and the developed countries modified their electricity markets. Developing countries are still at its infant stage of transition from producer oriented to prosumer oriented concept. There is not much study about the study of influence of prosumers in an oligopoly market. Hence, the bidding dynamics described developed for an oligopoly market is modified with the concept of prosumer and the developed Hybrid GPSO sliding mode controller is used to stabilize the chaos present in the bidding dynamics. This is the contribution from this chapter.

Chapter 9
Conclusions and Inferences

This chapter provides the summary of the work presented in this thesis along with discussions and conclusions of results obtained. The major contributions from the research work and the scope of future work are also detailed in this chapter.

9.1.Summary of the Work:

Restructuring of the power industry across the globe mainly aims at abolishing the monopoly in the generation and trading sectors, thereby, introducing competition at various levels wherever it is possible. Engineers in Electricity market operation have to consider the physical constraints of the power system, market operation rules, and financial issues. A clear understanding of the impact of power system physics on market dynamics and vice versa is necessary to address the new issues, such as oligopolistic nature of the market, supplier's strategic bidding, market power misuse, price - demand elasticity, which is arisen from the deregulation of the electricity sector. Theoretically, in a perfectly competitive market, the supplier should bid at their marginal production cost to maximize payoff. However, practically the electricity markets are oligopolistic in nature, and power suppliers may seek to increase their profit by bidding a price higher than marginal production cost. Knowing their own costs, technical constraints and their expectation of rival and market behavior, suppliers face the problem of constructing the best optimal bid. This is known as a strategic bidding problem. In general, competitive environment, like electricity market, requires good decision-support tools to assist players in their decisions. Relevant research is being undertaken in this field, namely in what concerns player modeling and simulation, strategic bidding and decision support for electricity markets in developed countries. In spite of all the recent achievements, there is still a deficit in terms of decision-support for electricity market players in developing countries. This deficiency is addressed by modeling the competitive bidding dynamics as an optimization problem. The analysis of real-time electricity market reveals the chaotic nature of bidding dynamics. The chaotic bidding dynamics is stabilized by designing a novel hybrid genetic particle swarm tuned sliding mode controller.

The power system industry has experienced tremendous modification in its structure and regulatory approach. Among these modifications, a drastic change is the transition from vertically integrated monopoly to a competitive market. Unlike other commodities, storage is not possible in the electricity market and hence proper analysis of price fluctuations and price analysis are highly essential for producers and consumers to adopt their own benefit and maximum utilization. There are very few studies related to the short term electricity price forecasting for developing countries, especially for the Indian scenario. During the first phase, the real data is collected from Indian day ahead electricity market and investigated its chaotic nature by adopting techniques from chaos theory. Based on Taken's theorem, phase space of the system is reconstructed. From the reconstructed phase space, a chaotic model, namely add weighted one rank multistep prediction model, is developed. The developed chaotic model outperforms other forecasting models like ARIMA, GARCH etc in terms of forecasting performances, computational complexity, and adaptability.

The ISO or power exchange often entertains bilateral contracts as long term contracts. Hence, there should be provisions for negotiation framework allowing the participants to prepare offers and counteroffers. Hence in phase II, a negotiation strategy is formulated. Market participants are heterogeneous and they follow their own interaction strategies. Producers pursue strategies that maximize profit while consumers adopt strategies that minimize their electricity cost. Customer strategies are associated with consumption efficiency. This represents actions related to the concepts of energy conservation, management and rational use of energy. In this way, demand response (DR) plays an important role in Energy management. Demand Management (DM) the capacity to manage electricity consumption of end use customers. This leads to overall price reduction, reliability benefits and altogether an improvement in Energy management performance. Based on the concept of demand response, a Buyer Motivated Negotiation Strategy (BMNS) is developed which consists of price strategy for the seller and volume strategy for the buyer. Simulation results prove the intellectual speculation that the behavior of market participants are as expected .The proposed BMNS method can be used as a simulation tool to help the decision process of negotiating agents during bilateral contracts in competitive electricity markets.

To ensure the social welfare, a regulatory model is mandatory. It is generally accepted that regulation is the second best alternative. It is best when the system can mimic the economic signals. Since mimicking the economic signals is very difficult in an electricity market, regulation model selection is a major concern. After evaluating the two existing regulation models, the research work evaluated the scope of Profit Ceiling Model (PCM) for electricity markets in developing countries.PCM regulation model incorporates the regulation aspects for investors and regulation on electricity price level. To regulate the electricity price level, the quantitative relation between average electricity price level and uplift is analyzed and it is inferred that the major concern with the regulation of electricity price is the uplift forecasting. Simulation results on the uplift forecasting of Indian Electricity market for the year 2014 demonstrate that Hybrid Genetic Particle Swarm optimization (GPSO) method is a best candidate for this optimization problem. Moreover, PCM introduces incentive mechanisms to reduce excess investment in new plants and profit sharing mechanism to remove extra profits in aged plants.

In the day ahead market, the bidders will submit their bids to the ISO, and then based on the submitted bids and demand function (i.e., by balancing supply and demand) the ISO determines the Market Clearing Price (MCP) and scheduled generation for the individual supplier. After the market is cleared, individual supplier knows the publicized MCP and his scheduled generation. Now in the next round of bidding, based on this information, he adjusts his generation bid to maximize his profit. Therefore the bidding dynamics can be considered as a dynamic feedback system. The generation decision process is very complex and one has to adjust this without knowing the strategies of his rivalries. In this research, state space model of bidding dynamics is proposed where the strategic variables of each producer is chosen as the state variables. In practical implementation, since the bidding dynamics strategic variables are chosen as state variables, producers may adjust their bidding dynamics to their optimum value (equilibrium point) by adopting the sliding mode controller. The value to be adjusted depends only on the sliding surface parameters which may be tuned effectively with the proposed GPSO algorithm.

As a modification to this bidding dynamics the concept of prosumer is introduced. The aim of the prosumer is to maximize their revenue or minimize the cost by exchange of energy to the market. The strategy adopted is that the prosumer are charged for their active and reactive power consumption at the rate of the MCP. To analyze the efficacy of prosumer oriented energy market, a scenario is generated where the producers are controlled by the hybrid GPSO tuned sliding mode controller and the prosumer bid is adjusted as an optimization problem. Under the simulated conditions, the modified prosumer bidding is economically beneficial and leads to either reduced price for the consumer or increased revenue for the prosumer. Moreover, the service rendered during the hours of stress may be beneficial even for other customers.

9.2. Major Contributions:

1. Design of a chaotic model for predicting the chaotic electricity price series.

    In the existing literature many methods are available for electricity price forecasting. Among these methods time series methods are found to be effective over other methods. Some research works report that high volatile time series may be predicted with chaos theory. Phase space reconstruction based on chaos theory is suggested in the literature. Using this theoretical background a chaotic model namely add weighted one rank multistep prediction model is developed for the electricity price forecasting for the developing countries, like India.

2. Design of Buyer Motivated Negotiation Strategy

    Demand response management is the new concept in power industry. Since the negotiation strategies adopted in financial markets are not as such appropriate in electricity market, a simple strategy based on DR management is developed. The proposed Buyer Motivated Negotiation strategy consists of a seller strategy and a buyer strategy. This is another contribution of this research work.

3. Formulation of a hybrid GPSO algorithm for optimization.

    The latest development in financial economics is Profit Ceiling Model (PCM). Many commodity markets adopted this model to incorporate incentive mechanism, profit sharing mechanism and to attract investment by reducing the risks faced by investors. The scope of PCM in regulating electricity market of developing countries is analyzed in this work. The major problem associated with PCM is the uplift forecast which can be treated as an optimization problem. Since the electricity market prices are highly fluctuating especially in developing countries, it is very difficult to solve this optimization problem using classical optimization solutions. Hence, a hybrid GPSO, which combines the merits of GA and PSO, is proposed to solve this optimization problem. This is an added contribution of this research work.

4. State space modeling of bidding dynamics in an oligopoly market and design of a Hybrid GPSO sliding mode controller to stabilize the chaos present in the bidding dynamics

Generally, the power bidding problems are addressed with game theory concepts. Due to the computational complexity associated with the discrete state concept, power bidding is viewed as a control problem. Even then, modern control techniques are never used to solve the bidding dynamics problem. However, the financial markets similar to electricity market which shows chaotic behviour is stabilized by using a sliding mode controller. In this context, the major difficulty is the design of sliding surface, specifically the tuning of sliding mode parameters. The major contributions in this area are threefold. These are (i) modeling of the power bidding dynamics of an oligopoly market with four producers in state space form; (ii) design of a sliding mode controller to stabilize the chaos present in the bidding dynamics, and (iii) formulation of a hybrid GPSO algorithm to tune the sliding surface parameters of the controller. Thus, the design of a Hybrid GPSO tuned sliding mode Controller to stabilize the chaos in electricity market bidding dynamics is one of the major contribution of this research work.

5. Modification of Bidding dynamics with Prosumer as one stakeholder

Concept of prosumer is the latest development in power system industry. The prosumer oriented market is accepted and the developed countries modified their electricity markets. Developing countries are still at its infant stage of transition from producer oriented to prosumer oriented concept. There is not much study about the study of influence of prosumers in an oligopoly market. Hence, the bidding dynamics described developed for an oligopoly market is modified with the concept of prosumer and the developed Hybrid GPSO sliding mode controller is used to stabilize the chaos present in the bidding dynamics. This is the last contribution of this research work.

9.3.Scope of Future work:

Since it is a pioneer work in the area of the sliding mode control of electricity market bidding dynamics in developing countries, this can act as a foundation for future work in this fraternity. Each and every chapter in this thesis can be explored further.

Moreover, two specified areas for future research are identified. These are:

1) Generally, combined heat and power (CHP) stations are participating in wholesale markets. While, solar photovoltaic systems are rarely participating in the whole sale markets. These solar systems affect the market operations indirectly by dipping the electricity demand during midday hours. From these observations, it is evident that a single approach is not appropriate to incorporate the distributed generation into the electricity market. As an alternative, a hybrid strategy with the coordination of centralized and distributed energy resources based on the localized peculiarities is to be developed. This problem is not addressed in this work and it remains as a future research area.

2) Another promising area is the influence of storage devices on electricity market. Due to the integration of renewable sources into electricity market, there may be lots of uncertainties in the generation/supply available in the market. This can be utilized effectively by allowing the owner of a storage resource to disaggregate these various services and sell them each to a third party for the transaction in markets. This could induce more optimal use of storage options. This concern also may be addressed by a future research work.

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List of Publications

1. **International Journals:**

    a. Indhu Nair, Anasraj R., **"A Chaotic model Approach for Electricity Price Forecasting In Indian Scenario", International** Journal on Computational Economics and Econometrics, vol.4, 2017, pp: 443-453. DOI: 10.1504/IJCEE.2017.10003512

    b. Indhu Nair, Anasraj R., **"Design of a Buyer Motivated Negotiation Strategy for Bilateral Contracts in Electricity Market"**, Energy Policy, Elsevier (status: accepted)

    c. Indhu Nair, Anasraj R., **"Genetic Particle Swarm Tuned Sliding Mode Controller for Chaotic Bidding Dynamics in Oligopoly Electricity Market",** IEEE Transactions on Power System.(status: under review)

2. **International Conferences:**

    a. Indhu Nair, Anasraj R., "**Hybrid Genetic Particle Swarm Tuned Sliding Mode Controller for Chaotic Finance System** ," IEEE Conference on Advances in Computing, Communications and Informatics (***ICACCI***) , 2014, pp: 1290 - 1295 DOI: 10.1109/ICACCI.2014.6968261

    b. Indhu Nair, Anasraj R., **"Design and Analysis of Profit Ceiling Model for Regulating Electricity Market in Developing Countries"**, IEEE Power and Energy Society Conference ICUE2016, Sept 14-16, at Bangkok, pp.1-6. DOI: 10.1109/COGEN.2016.7728962