Bidding Strategies in an Emerging Electricity Market

Ph.D. Thesis

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Declaration

I, **Satyendra Singh** declare that this thesis titled, ***"Bidding Strategies in an Emerging Electricity Market"*** and work presented in it, is my own. I confirm that:

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- Where any part of this thesis has previously been submitted for a degree or any other qualification at this university or any other institution, this has been clearly stated.
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December 2019

The thesis is dedicated to

My father (late) Sh. Shakti Singh who taught me the virtues of discipline, honesty and sincerity.

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(Satyendra Singh)

Abstract

THE materialization of deregulation has erected vast structural changes in electrical power system operation. It has evolved the system from vertical integrated utilities to decentralized control, which led to growth of multiple power producers in the scale of small to large power generation. This liberalization of power sector has emerged electricity market to increase competition amongst power suppliers for benefiting consumer needs. Though, the electricity market structure is more like oligopoly than perfect market due to various limitations of the power suppliers such as: low in numbers, hefty investment (entry barrier), lack of transmission infrastructure and their location. These all limitations require an effective way by constituting a competitive environment through strategic bidding where suppliers and buyers negotiate price termed as market clearing price (MCP) at demanded power.

This thesis presents bidding strategies for profit maximization of market participants in an emerging power market, with and without amalgamation of renewable energy sources, under different energy trading schemes. These bidding strategies has been effectively solved by an improved version of a meta-heuristic technique Gravitational Search Algorithm (GSA) called as Oppositional Gravitational Search Algorithm (OGSA) in single side bidding. And in double side bidding a hybrid approach Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) in combination of OGSA known as TOGSA is utilized to solve multi-objective problem. In addition, the coordinated bidding strategy between energy and reserve markets is also presented for profit maximization of power suppliers in single side bidding with the application of OGSA.

In single side trading mechanism, power suppliers (PSs) send an offer to the Independent System Operator (ISO). The PSs optimize their bidding information with a profit maximization goal before submitting the offers to pool operators and then submit the optimized offers to the ISO. This task is called the "maximization of the supplier profit". These PSs can also calculate the bidding value of the rival by using the joint Probability Distribution Function (PDF) in the bidding strategy process. The market behaviour is demonstrated in the oligopoly environment. The PSs, who try to maximize their profit, use OGSA to optimize their bid value. This algorithm's efficacy is evaluated using IEEE standard 30-bus system in a single-hour trading period and six generating units with considering ramp rate constraints in multi-hour trading periods. The objective of bidding strategy in double side trading mechanism is to maximize the social welfare. PSs and also large customers are permitted to submit their bids to a central pool operator in a double-side

centralized trading mechanism. When both PSs and large customers are participated in double sided bidding for profit maximization, problem becomes a multi-objective in which two objectives are simultaneously optimized. Both objectives for profit maximization of PSs and large customers are conflicting in nature, this is because, the energy providers attempt to raise the MCP by withholding ability from the market and the big customers attempt to lower the MCP by changing their power consumption. Therefore, effectiveness of TOGSA is evaluated on the system having six power suppliers and two large consumers participating in a single hour trading period.
The bidding in electricity market using conventional power suppliers is a deterministic approach due to well-known availability of resources. However it is not a case with renewable based resources whose uncertainty and variability can cause unforeseen situation in the system. This thesis attempts an approach to include wind and solar based resources with conventional resources in electricity bidding. For this a probabilistic models are utilized for modeling of wind and solar, and a scenario generation and reduction method Kantorovich Distance Matrix (KDM) is employed to model variability of resources. An appropriate mathematical model is proposed for MCP calculation in the presence of renewable energy sources. The effect of the renewable energy sources is tested on the both single and double side bidding mechanisms in a single hour trading period. It is observed that amalgamations of wind and solar power can affect the offer from the outcomes acquired as it decreases the conventional power suppliers (CPSs) generation and offers less MCP value that would supply adequate electricity from approved sales offers to satisfy all approved purchase offers and boost the total traded energy.

The same operation discussed in single side trading mechanism will be repeated for coordinated bidding strategy between energy and reserve markets for profit maximization of power suppliers participating in a single hour trading period. The proposed method is tested on six PSs system considering one supplier as main generator and other five as its rival generators. Estimated output limit of spinning reserve for sixth supplier is to be really used as 0.1 and 0.2 times of required spinning reserve capacity broadcast by the ISO respectively. Using OGSA, the bid coefficients are optimized. The simulation results validate the efficacy of OGSA in providing better optimal solutions.

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Abbreviations

BPDF	**B**eta **P**robability **D**istribution **F**unction
CPS	**C**onventional **P**ower **S**upplier
CPSs	**C**onventional **P**ower **S**uppliers
GA	**G**enetic **A**lgorithm
GENCOs	**G**eneration **C**ompanies
GSA	**G**ravitational **S**earch **A**lgorithm
IMCRs	**I**mbalance **C**ost **R**enewables
ISO	**I**ndependent **S**ystem **O**perator
KD	**K**antorovich **D**istance
KDM	**K**antorovich **D**istance **M**atrix
LBs	**L**arge **B**uyers
MC	**M**onte **C**arlo
MCP	**M**arket **C**learing **P**rice
NIS	**N**egative **I**deal **S**olution
OBL	**O**ppositional **P**opulation **B**ased **L**earning
OCRs	**O**verestimation **C**ost of **R**enewables
OGSA	**O**ppositional **G**ravitational **S**earch **A**lgorithm
PDF	**P**robability **D**istribution **F**unction
PIS	**P**ositive **I**deal **S**olution
PRs	**P**rofit **R**enewables
PSO	**P**article **S**warm **O**ptimization
PSs	**P**ower **S**uppliers
PX	**P**ower **E**xchange

RCI	**R**elative **C**loseness **I**ndex
RESs	**R**enewable **E**nergy **S**ources
RGA	**R**efined **G**enetic **A**lgorithm
RPG	**R**enewable **P**ower **G**eneration
RPS	**R**enewable **P**ower **S**upplier
SBP	**S**trategic **B**idding **P**roblem
SD	**S**tandard **D**eviation
SPVs	**S**olar **P**hoto **V**oltaics
TOPSIS	**T**echnique for **O**rder of **P**reference by **S**imilarity to **I**deal **S**oltuion
TP	**T**otal **P**rofit
TPG	**T**otal **P**ower **G**eneration
TPT	**T**otal **P**ower **T**raded
UCRs	**U**nderestimation **C**ost of **R**enewables
WPDF	**W**eibull **P**robability **D**istribution **F**unction

Symbols

$\alpha_{m,t}$, $\beta_{m,t}$	Bidding coefficients of m^{th} power supplier which must be non negative
γ	Shear coefficient, which depends on surface roughness and atmosphere stability
$\phi_{n,t}$, $\varphi_{n,t}$	Bidding coefficients of n^{th} large buyer which must be non negative
υ^i, υ^j	Scenarios for renewable
$\rho_{m,t}$	Correlation coefficient between $\alpha_{m,t}$ and $\beta_{m,t}$
$\rho_{n,t}$	Correlation coefficient between $\phi_{n,t}$ and $\varphi_{n,t}$
ρ	Density of air at the wind location (kg/m^3)
$\eta_p\left(v\right)$	Total efficiency of the wind generator communicated as a function of wind speed
A_t, B_t	Parameters for Beta PDF
A_s	Rotor swept area of the wind turbine
c	Scale factor
$CD_{n,t}$	Active power demand by n^{th} large buyer at t^{th} hour in double side bidding (MW)
$D\left(R_{s,t}\right)$	Load forecast by ISO in single side bidding (MW)
$D\left(R_{d,t}\right)$	Load forecast by ISO in double side bidding (MW)
$D_{c,t}$	Constant Number
h_g	Hub height of generator (m)
h_{kah}	Anemometer height (m)
$IMC(Wg_n)$	Imbalance cost for wind generator (\$)
$IMC(Sg_n)$	Imbalance cost for solar generator (\$)
I_{mpp}	Current at maximum power (Amp.)
I_{sc}	Short circuit current of PV cell (Amp.)

I_{TK}	Current temperature coefficient (mA/degree centigrade)
K	The load-price elasticity of electricity
k	Shape factor
K_u	Penalty cost for situation profit loss per \$/kWh due to renewable power overestimation
K_o	Penalty cost for purchasing power from reserve per \$/kWh due to renewable power overestimation
m	Number of power suppliers participating in bidding process
n	Number of large buyers participating in bidding process
$O_c(w_g)$	Overestimation cost for wind generator (\$)
$O_c(S_g)$	Overestimation cost for solar generator (\$)
$PG_{s,m,t}$	Active power generation by m^{th} power suppliers at t^{th} hour in single side bidding (MW)
$PG_{d,m,t}$	Active power generation by m^{th} power suppliers at t^{th} hour in double side bidding (MW)
$PG_{\min,s,m,t}$	Minimum active power generation by m^{th} power suppliers at t^{th} hour in single side bidding (MW)
$PG_{\max,s,m,t}$	Maximum active power generation by m^{th} power suppliers at t^{th} hour in single side bidding (MW)
$PG_{\min,d,m,t}$	Minimum active power generation by m^{th} power suppliers at t^{th} hour in double side bidding (MW)
$PG_{\max,d,m,t}$	Maximum active power generation by m^{th} power suppliers at t^{th} hour in double side bidding (MW)
$P^{e}_{\min,m}$	Minimum active power generation in energy market (MW)
$P^{e}_{\max,m}$	Maximum active power generation in energy market (MW)
$P^{sr}_{\min,m}$	Minimum active power generation in spinning reserve market (MW)
$P^{sr}_{\max,m}$	Maximum active power generation in spinning reserve market (MW)
$PC_{s,m,t}(PG_{s,m,t})$	Production cost function of m^{th} power supplier at t^{th} hour in single side bidding
$PC_{d,m,t}(PG_{d,m,t})$	Production cost function of m^{th} power supplier at t^{th} hour in double side bidding

$PC_{d,n,t}(CD_{n,t})$	Purchasing cost function of n^{th} large buyer at t^{th} hour in double side bidding
$R_{s,t}$	Market Clearing Price in single side bidding at t^{th} hour (\$/MW)
$R_{d,t}$	Market Clearing Price in double side bidding at t^{th} hour (\$/MW)
R_e	Market Clearing Price in energy market (\$/MW)
R_{sr}	Market Clearing Price in spinning reserve market (\$/MW)
RD_m	Maximum downward ramp rate of m^{th} power supplier
RU_m	Maximum upward ramp rate of m^{th} power supplier
$S_{i,t}$	Solar irradiance at time interval t
S_g	Schedule solar generation (MW)
S_a	Available solar power (MW)
t	Time in hour
T	$1, 2, ..., 24$
T_a	Ambient temperature ^{0}C
T_{NO}	Nominal cell temperature (degree centigrade)
$T_{cell,t}$	Cell temperature at time interval t (degree centigrade)
$U_c(w_g)$	Underestimation cost for wind generator (\$)
$U_c(S_g)$	Underestimation cost for solar generator (\$)
v_{in}	Cut-in wind speed (m/s)
v_r	Rated wind speed (m/s)
v_o	Cut-off wind speed (m/s)
v	Recorded wind speed in meter per second (m/s)
$v\,(h_{est})$	Predictable average speed of wind (m/s)
$v\,(h_{rkh})$	recorded speed of the wind at known hub heights (m/s)
V_{oc}	Open circuit voltage of PV cell (V)
V_{TK}	Voltage temperature coefficient (mV/degree centigrade)
V_{mpp}	Voltage at maximum power (V)
W_r	Rated output of the wind generator (MW)
$W_a\,(v)$	Available wind power at recorded wind speed (MW)
W_g	Schedule wind generation(MW)
W_a	Available wind power (MW)
x	Number of renewable power supplier participating in bidding process

Chapter 1

Introduction

1.1 Introduction

THE bidding strategies employed by different market entities in an emerging power market environment can also have substantial influences on their profits/benefits and a power market's operating behaviour. Electrical utilities have been or are being restructured in many countries. Restructuring has many reasons. It can be driven by the government's desire to meet the growing demands for electricity by promising independent power generation, which supports the government from financial compulsion [1]. It enables consumers to select their electrical supplier based on the offered price and service. The dramatic changes in electric utility organization bring new challenges and opportunities with them. Thus, competitive framework replaces the previous centrally designed and operated systems. Restructuring has introduced the disintegration of the three electric power industry activities such as generation, transmission, and distribution [2]. Also, this framework has established open and competitive electricity market activities for electrical power trading. All these activities have undergone substantial processes of transformation in the restructured environment to find a more secure, reliable and economical operating range [3]. For the entire system, a system operator is appointed, which commended with accountability for maintaining the system in balance, *i.e.*, ensuring that production and imports continuously matched consumption and exports. Logically, system operator should work independently, neither involving in market competition, nor own business generation facilities (Expect for having some emergency capacity) [4].
The establishment of an electricity market has two main objectives [5]

1. To ensure a secure operation: The most important aspect of power system operation is security, whether it is a regulated operation or a restructured power market. Security could be facilitated in a restructured environment by using the diverse services available to the market.

2. To facilitate an economic operation: The electricity market's economic operation would reduce the cost of using electricity. This is a primary motive for restructuring and a way through its economics to enhance the security of a power system.

To do this, appropriate strategies must be developed in markets based on the requirements of the power system. At present, many electricity markets around the world are moving towards more deregulated and competitive markets. The modifications were initiated by

1. It is not necessary to carry out generation and distribution functions as monopolized;

2. The competitive cost reduction potential;

3. Increased stability of fuel and fuel supply; and

4. Developing new methodologies for power generation and information technology.

Competition is essential in market restructurings, also cost reduction and efficiency are often preferred. It will result from private entities being carefully regulated and enable them to access the market. It can be introduced solely for the accumulation of new generating capability called competitive bidding in which the existing company is inviting contractors to construct, operate and sell electricity at a specified price to the monopoly. Cost savings, spot market development, standards of service match consumer preferences and innovations are the main advantages of competition.

1.2 Types of Restructured Electricity Market

On the basis of trading in this work two types of market are considered namely energy market and market for ancillary services in a day-ahead market. Day-ahead market is used in the most electricity markets for scheduling resources at every hour of the next day. Both energy and ancillary services can be traded in forward markets. The day-ahead energy market is generally cleared first. Then bids are submitted for ancillary services, which can be cleared sequentially or simultaneously. The Independent System Operator (ISO) would offer ancillary services by auction wise arrangement whenever energy schedules can be accommodated in a day-ahead market without congestion management. It is important to note that markets are interrelated rather than independent [1–5]. In the following sub-sections, organization of the type of the markets has been discussed

1.2.1 Energy Market

Energy market is the market place for competitive trading of electricity. It is a centralized mechanism that creates it easier for buyers and sellers to trade in energy. The prices of the energy market are reliable indicators of prices, not only for market participants but also for other financial markets and electricity consumers. The energy market has a settlement and clearing function that is neutral and independent. The energy market is generally operated by the ISO or the Power Exchange (PX). The ISO (or PX) receives market participants' generation and demand bids (quantity and a price pair) in the energy market and decides the market-clearing price (MCP) at which energy is traded. Usually, the definition of the MCP is as follows: add the bids of supply to the supply curve and add the bids of demand to the demand curve. The supply curve and demand curve intersection point is called the MCP.

1.2.2 Ancillary Services Market

Ancillary services are the facilities needed to support electrical power transmission from supplier to buyer in view of the control area obligations and transmission of utilities to retain the reliable operation of the interconnected transmission system within those control areas. These services are bundled with energy in the regulated electricity market and un-bundled from energy in the deregulated electricity market. Also, these services are competitively procured in the market. Competitive markets for ancillary services operate in California, New York, and New England in the United States. In general, market participants submit ancillary services bids consisting of two parts: a capacity bid and an energy bid. Offers to ancillary services are usually cleared in terms of bids for capacity. The bid for energy represents the willingness of the participants to be paid if the energy is actually supplied. Various ancillary services could be cleared sequentially or simultaneously in the deregulated electricity market. A market is cleared for the highest quality services in the sequential approach first, then the next highest, and so on. Consequently bids for ancillary services would be submitted by the market participants in the simultaneous approach and ancillary services market would be cleared by the ISO (or PX) simultaneously by evaluating the problem of optimization.

1.3 Competitive Bidding

Sellers and buyers submit bids for energy buying and selling in a competitive electricity market. There is also a provision for simultaneous bidding for energy reserves in some markets, for example in New Zealand and CAISO. The bids are normally estimated in terms of price and capacity and specify how much and at what price the seller or purchaser is willing to sell or purchase. Once the market operator has received the bids, it settles the market on the basis of a criterion. After the market has been cleared, all participants who sell, receive a uniform price for their delivered power, i. e., the market price from the buyers [2].

1.3.1 Strategic Bidding

Building suitable bids is very important for electricity market participants as their underlying goal is to maximize profits. Strategic bidding is dependable with system operating principles and participants usually have the freedom to bid at different prices than their costs. The importance of strategic bidding is outline below:

1. Strategic bidding effectively decides the MCP on the basis of supply and demand bids, and as a result, it helps the traders to maximize their overall profits.
2. The per capita consumption and generation of energy in the electric power system will increase and load shedding will reduce considerably as the strategic bidding helps to decide the desired MCP considering both suppliers, as well as, buyers.
3. Strategic bidding adequately restricts the abuse of market power due to existing loopholes. This phenomenon can be further utilized in market structure and management rules since these results have important policy implications.

1.3.2 Strategic Bidding Clearing Models

Several models for the market structure were considered to achieve the market goals for electricity. The following three basic models [6] are outlined below. Trading arrangements in deregulated power system is shown in Figure 1.1.

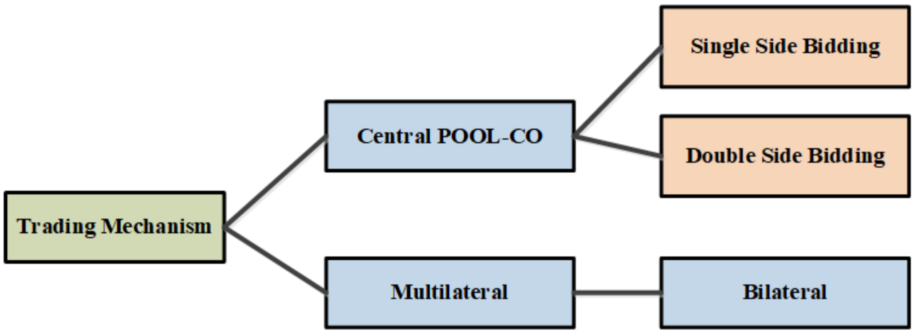


FIGURE 1.1: Trading arrangements in deregulated power system

1. POOL-CO Model: A centralized marketplace in which buyers and sellers clear the market is known as POOL-CO model. Single and double sided bidding are organized in this type of model. In a single sided bidding model, only generators bid several energy price segments depending on the amount of energy supply, at individual generating companies (GENCOs) own discretion, for every trading interval. On the other hand, in double sided bidding model, ISO clears the market in a centralized marketplace to manage the entire system through bids from both the sellers and the buyers and also maintaining the system reliability and operation of the electricity market. Sellers and buyers of electricity submit bids to the pool for the quantities of power they are willing to trade on the market. Sellers in a power market would compete, not for specific customers, for the right to supply energy to the grid. It may not be able to sell if a market participant bids too high. On the other hand, buyers are competing for buying power, and they may not be able to buy if their bids are too low. Basically, low-cost generators would be rewarded in this market. An ISO in a POOL-CO would implement the economic dispatch and generate a single (spot) electricity price, giving participants a clear signal for consumer and investment decisions. In the electricity market, the dynamics of market would drive the spot price to a competitive level equal to the most efficient bidders' marginal cost. Winning bidders are paid the spot price in this market which is equal to the winners' highest bid. Figure 1.2 shows the basic structure of the pool-co model.

2. Bilateral Models: Bilateral models are negotiable contracts between two traders on the delivery and receiving of power. In this model, buyers and sellers do trading based on their agreements which is independent from the ISO. However, ISO confirms the availability of sufficient transmission capacity in order to maintain the security of the system. As trading parties specify their desired contract terms, the bilateral contract model is very flexible. However, its drawback is stems from high negotiation and

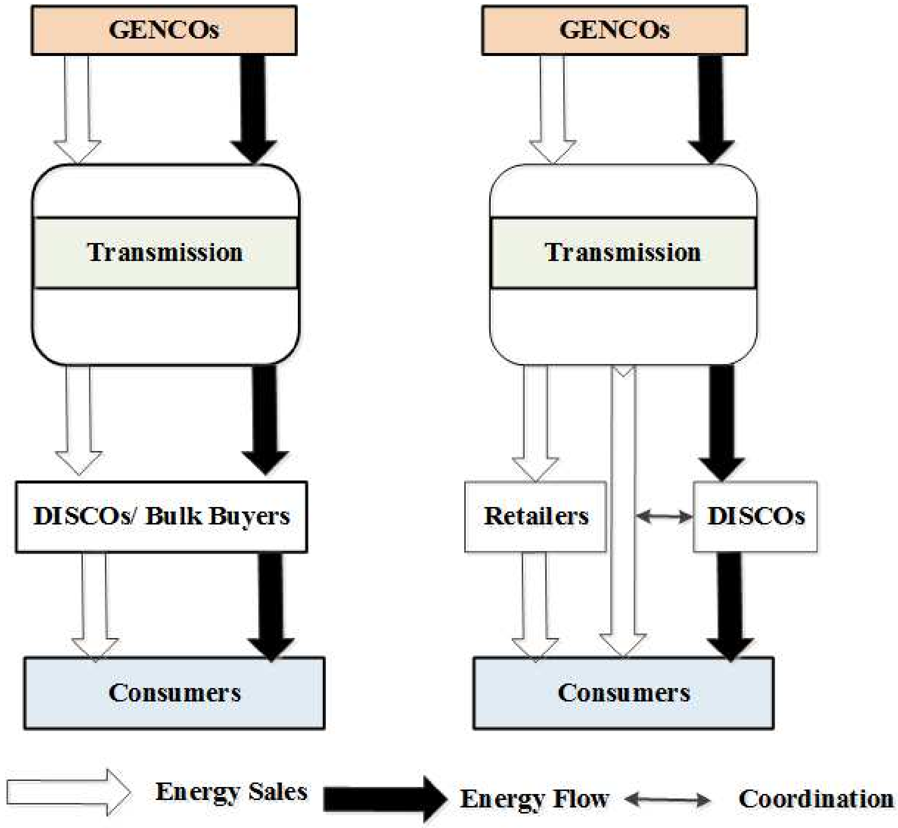


Figure 1.2: Trading in power pool

contract writing costs and the risk of counter party creditworthiness. Figure 1.3 shows the bilateral market structure.

3. Hybrid Model: The hybrid model is the combination of the different characteristics of the POOL-CO and bilateral models. The use of a POOL-CO is not mandatory in this model, and any customer may directly negotiate contract of the power supply with suppliers and select power at the price of the spot market. POOL-CO would help all participants (buyers and sellers) in this model who does not select to sign bilateral agreements. However, enabling customers to negotiate power procurement provisions with suppliers would provide a real choice for customers and push to the development of a wide range of services and choices for pricing to best meet customer requirements. Figure1.4 shows the hybrid market structure.

Out of the above described models, POOL-CO model is considered in this work.

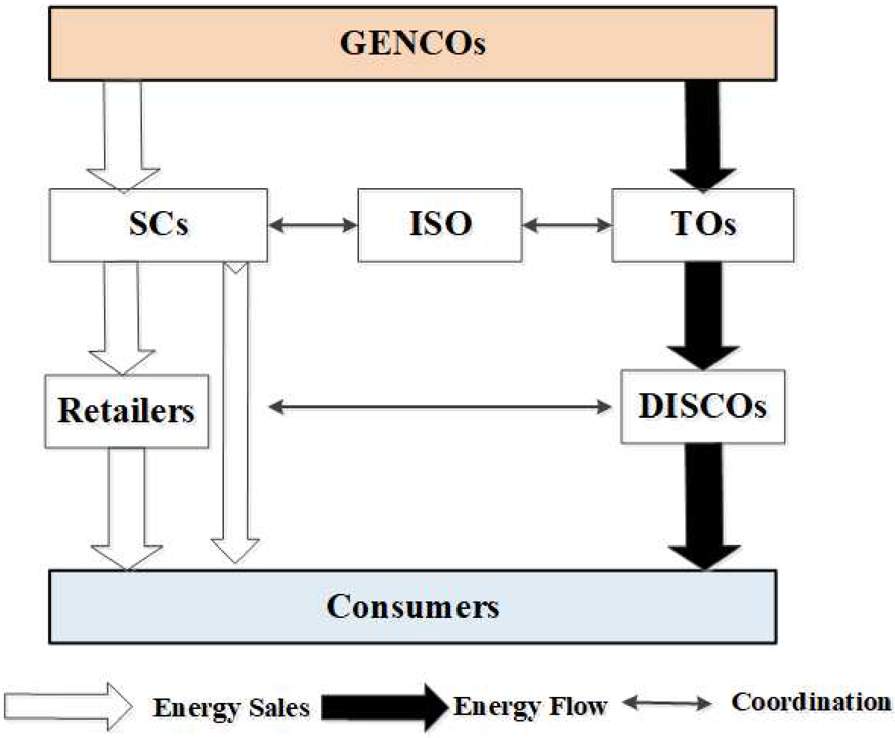


FIGURE 1.3: Trading in bilateral market

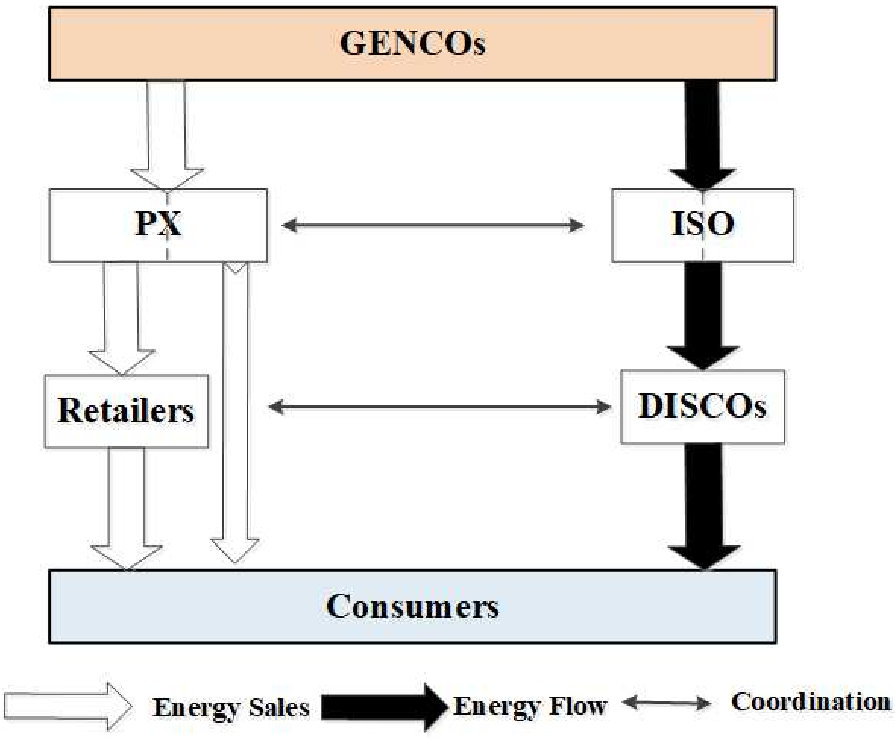


FIGURE 1.4: Trading in hybrid market

1.3.3 Key Components in Strategic Bidding Procedure

The electric industry's setup has changed from a vertically integrated manner to a competitive market manner globally. The generation, transmission and distribution activities were managed and functioned in the traditional system by a single, centralized utility operator that ensures energy flow to customers throughout the service area. Operation of the vertically integrated power system is based on achieving possible cost-effective solution while meet the requirements of security and reliability. But there are different problems associated with deregulated power industry and new system operation standards. Because, in the deregulated market, numerous entities are developed. Several system operation activities were taken over by many entities such as GENCOs and the market operator. In this market, everyone has to play independently while maintaining system reliability and security. In the power market, GENCOs, customers and ISO are key players [2, 5].
The main goal of GENCOs is to maximize their own profit. Due to this reason, firstly, the GENCO must make a precise system forecast, containing its price and its load. Secondly, the GENCO should have a good bidding strategy based on the forecasted system information in order to achieve the maximum profit.
In a restructured system, customers are no longer obligated to purchase any services from their local utility company. Customers would have direct access to generators or contracts with other providers of power, and choose packages of services (e.g., the level of reliability) with the best overall value that meets customers' needs.

ISO plays a major role in market operations as well as in security operations in deregulated electrical power systems operating with the pool type of structure [7]. Also, ISO's responsibilities are to operate the market in a safe and efficient manner and to monitor the market free of market power. Therefore, first, the ISO must accurately predict the system load to ensure that there is sufficient energy to satisfy the load and sufficient ancillary services to ensure the physical power system's reliability. Second, the ISO's operational responsibilities include the energy market, the market for ancillary services, and the market for transmission. To fulfill these responsibilities, ISO must be equipped with powerful tools. Third, to suppress market power and protect market participants, the ISO must be equipped to monitor the market.

1.4 Literature Review Focused on Bidding Strategies in an Emerging Electricity Market

The power system restructuring has changed the power system function significantly, resulting in significant competitive, technological and regulatory modifications. In deregulated markets, the function of strategic bidding plays a vital role in optimizing the profit of the competition participating entities [8]. Moreover, Strategic bidding problems from the point of view of power suppliers and large buyers, this type of transition is also justified by the current situation as an inevitable social welfare necessity. Therefore, in the economic operation of deregulated power systems, strategic bidding problems in the auction markets play an important role. In recent times many researchers have carried out their research over strategic bidding.

The power supplier (PS) is a price-taker in a perfect electricity market. For a supplier, the optimal bid strategy is simply to bid marginal costs. When a power supplier bids to exploit market imperfections to increase profits other than marginal production costs, the behavior is called strategic bidding [9, 10]. If the power supplier can increase its profits successfully through a strategic bid or any other way than to reduce its costs, it is said that it has market power [9]. The emerging markets for electricity are certainly not perfectly competitive, resulting in a supplier being able to increase profits through strategic bidding or, in another way, through exercising market power. The problem of optimal bidding strategies for competitive PSs was first introduced by David [10] and the author observed that there was some factor that may influence these bidding strategies. Some of them are rival's behaviour, supplier production cost, deviation in demand, and operating constraints or some regulatory constraints. Among these, most uncertain is the bidding behaviour of rival suppliers due to the natural behaviour of members who play to expand their benefit. This may intensify the troubles in bidding decision process. In [11], [12], authors have assumed that the electricity providers are free to charge their marginal production expenses and submit single hour [11] and multi hour [12] linear bidding features, and are paid the MCP once their offers have been selected. The bidding issues are formulated as a stochastic optimization operation and solved by using Monte Carlo (MC) [11] and Refined Genetic Algorithm (RGA) [12], respectively. Moreover, in these works rivals bidding behaviours are presented as a discrete nature. Therefore, a comprehensive work has been done on the development of strategic bidding while considering the generation side participation. In [13], authors study the spot market bidding decision-making issue and to calculate the probabilities of change and benefits for the Markov Decision Process

(MDP) model, an algorithm is created. A conceptual research is conducted on the procurement policies of energy providers in electricity market, using the step-by-step procurement protocol [14]. A uniform price spot market in which all winning supply bidders receive the same price for market clearing and other competing generators' offers (rivals) are based on the features of probability distribution is considered in [15]. In [16], authors have suggested to apply the Particle Swarm Optimization (PSO) technique for strategic bidding on the oligopolistic power market by an electricity provider. For both block bidding and linear bidding, the power market model was postulated. Optimization model for Strategic Bidding Problem (SBP) is proposed in [17] and show how to fix it using a decomposition-based PSO technique. The inertia weight approach particle swarm optimization (IWAPSO) has been proposed to solved optimal bidding strategy for power suppliers and the anticipated maximization of profit and minimization of risk (profit variance) are mixed into the objective function of the issue of optimization in [18]. The Ant Colony Optimization algorithm was suggested to model the bidding behaviours of power market providers with a step-by-step bid function in [19]. In [20], authors have proposed a new technique using a combination of PSO and Simulated Annealing (SA) to predict the Generating Companies (GENCOs) bidding approach in the electricity market where they have incomplete information about their rivals and the industry payment mechanism is paid as an offer. A novel self-organizing hierarchical particle swarm optimization with time-varying acceleration coefficients (SPSO-TVAC) solves the objective function of the GENCO including the anticipated profit maximization and risk minimization and the MC strategy is used to simulate the conduct of competitors in [21]. From a GENCO's point of view, Genetic Algorithm (GA) has been proposed in [22] for bidding approach in a day-to-day market to maximize one's own profit as a market participant. Fuzzy Adaptive Gravitational Search Algorithm (FAGSA) has been presented to solve the optimum bidding strategy problem in a pool-based electricity market in [23]. The optimal bidding strategy problem has been solved by using shuffled frog leaping algorithm (SFLA) in [24, 25]. in [26], authors have presented various metaheuristic algorithms such as GA, SA and HSAGA to simulate wholesale electricity bidding strategies using the Nash equilibrium idea and compare the algorithm efficiency. A Global Self-Adaptive Harmony Search Algorithm (SGHSA) is used to achieve optimum bidding approaches in [27]. Differential Evolution (DE) algorithm is proposed to solve the problem of bidding strategy in the operation of power systems in a deregulated environment in [28]. Invasive Weed Optimization Algorithm (IWOA) has been implemented to tackle the issue of the optimal bidding strategy in [29]. It is worth mentioning that in the above discussed literature, heuristic and metaheuristic approaches have been adopted to solve the different strategic bidding problems. Also, rivals' bidding behaviors are represented as a discrete probability distribution function. Moreover, supplier profit maximization objective function represented as non-linear due to unknown or stochastic bidding parameters. Therefore, depending on the bidding models, objective function and constraints may not be differentiable; in that case conventional methods cannot be applied, whereas, heuristic and metaheuristic methods could be applied [23]. Heuristic and metaheuristic methods are basically based on the tuning of its parameters and thus the techniques having less tuning parameter results in the most accurate results. The trend of hybridizing and metaheuristic algorithms has been increased over the years. Beside this linear, block and step wise bidding function with the generation limit constraints have also been considered in strategic bidding problem. This consideration is not pragmatic as real-time generation is limited by ramp rates; this would affect the operation of generating units [30], [31], which is critical to ensure practical optimal results. Thus, to obtain the practical optimal solution, the generators with ramp rates consideration are essential.

In the literature, most of the researchers have focused on supplier's side strategic bidding problem; limited work has been carried out on the demand side. Based on this, [32] proposed a strategic bidding problem together for power suppliers and large consumers. Thereafter, [33–38] attempted and solved the problem of PS and large buyer profit maximization by determining both entities bidding parameters. In an emerging power market, when both entities; suppliers and buyers; participate in double sided bidding for profit maximization, problem becomes a multi-objective strategic bidding problem in which two objectives are simultaneously optimized. This is because of the nature of the power suppliers and buyers. The power suppliers try to increase the MCP by withholding capacity from the market and the large buyers try to decrease the MCP by adjusting their power consumption. As these objectives are contradictory, a specific multi-objective problem design is essential. By assigning weights [39–42] or multiplying them with a penalty function [43], many multi-objective formulations considering multiple goals are converted into a single-objective problem. The normally utilized structures for multi-objective formulation may incorporate weighted sum [39–42], goal programming [44], penalty function [43], epsilon-constrained [45] based methodologies. However, these techniques have a few restrictions, for example, the ideal arrangement of the weighted sum methodology relies upon the choose weights, pre-specified goals must be allotted in goal programming, and a master and slave goals are required to be determined in epsilon constrained approaches. The above discussed methods suffer from some more limitations which can be overcome by scaling the objectives through the different approaches like fuzzification [46], max–min approach [47], and fuzzy-based goal programming [48], but they may be lacking the inbuilt mechanism to deliver the desired Pareto-front. Therefore, more powerful multi-objective solution approaches are required.

During the recent years, the renewable energy usage around the globe has been on the upward swing due to low carbon emission. Electrical power productions and percent of installed capacities of wind and solar power plants go higher and will turn into the significant power generators soon. Owing to this reason, Renewable Energy Sources (RESs) are under prime concern with the annihilation of fossil fuels along with carbon emissions. This has led to new dimensions of exploration in optimal bidding strategy with amalgamation of wind and solar based power generation, which further draw the interest of researchers. As a part of the strategic bidding of conventional generators, the GENCOs having renewable generation also participates in the bidding process. It provides market fairness and better utilization of RESs in the deregulated market [49]. Wind and solar power generation have been the first choices due to its low cost, among all types of RESs. The main disadvantages of wind and solar power production are its uncertainty and unpredictable nature of wind speed and solar irradiations which always result in deviation from the actual generation. In the deregulated environment, the uncertainties of wind and solar power have increased the problems manifold for the producers in devising an optimal bidding strategy with CPS. A comprehensive work has been done on the development of strategic bidding while considering the wind PSs participation. A bidding strategy considering wind PSs with conventional generators in a deregulated electricity market is proposed [50–52]. The effect of wind generation on electricity prices has been investigated by [53]. However, the variability has not been evaluated by considering any uncertainty model in [50–53]. Moreover, [54] has considered a probabilistic strategy for evaluating the electricity cost in the market for wind generators associated with wind prediction errors. On the basis of the concept presented in [54], the penalties associated with the deviation between forecasting and actual production of wind power is considered in [55–57]. Uncertain wind power output increases the imbalance cost and penalties associated with wind farms. This result reduces the revenue for wind PSs. Other renewable power sources such as Solar Photovoltaics (SPVs) have also been considered in bidding strategy [58–62]. However, these works have not considered uncertainty associated with SPV. The main disadvantages of wind and solar power production are its uncertainty and unpredictable nature of wind speed and solar irradiations which always results in deviation from the actual generation. In the deregulated environment, the uncertainties of wind and solar power have increased the problems manifold for the producers in devising an optimal bidding strategy with CPS. Uncertain wind and solar power output increases the imbalance cost and penalties associated with wind and solar farms. This result reduces the revenue for wind and solar

PSs. Therefore, the actual modeling of the uncertain wind power is essential to minimize the imbalance and increase the profit.

The deregulated electricity markets raise the importance of coordination of bidding strategies in the energy and reserve services market. The effect of coordinated bidding strategies in the energy and reserve services market has been investigated by many researchers. In these two markets, the single sided bidding is utilized in which an energy prices inclusive of other cost either fixed or variable is offered, and a simple market clearing process based on the intersection of supply and demand bid curves is used to determine the winning bids and schedules for each hour. The problem of developing optimally coordinated bidding strategies in day-ahead energy and spinning reserves for competitive power suppliers has been presented in [63]. Furthermore, assumed that energy market and reserve market is cleared independently and simultaneously for 24 supply hours [64] and single supply hours [65]. Thereafter, [66–71] attempt these problems for profit maximization of the power suppliers in energy and reserve market and an extensive review of different modeling and dispatching method for focusing energy and reserve markets is presented [72] and concluded that the inclusion of additional variables and constraints significantly increases the size of the problem and hence the expected calculation times. These disadvantages will certainly be some of the challenges facing future work.

1.5 Research Objectives

Based on the literature survey, the particular objectives of this work are:

1. To develop single side bidding strategy for profit maximization of power suppliers participating in a single hour trading period.

2. To develop single side bidding strategy for profit maximization of power suppliers participating in multi hour trading period considering ramp rate constraints.

3. To develop double side bidding strategy for profit maximization of power suppliers and large buyers participating in a single hour trading period.

4. To develop single side bidding strategy for profit maximization of power suppliers with amalgamation of renewable energy sources participating in a single hour trading period.

5. To develop double side bidding strategy for profit maximization of power suppliers and large buyers with amalgamation of renewable energy sources participating in a single hour trading period.

6. To develop coordinated bidding strategy between energy and reserve markets in a single hour trading period.

1.6 Thesis Contributions

This study takes the restructured electricity market operation considering the strategic bidding problem only. Strategic bidding in restructured electricity markets are further confined into strategic bidding in single sided POOL-CO model, double sided POOL-CO model with and without amalgamation of renewable energy sources and coordinating bidding strategy between energy and reserve markets.
Strategic bidding models appropriate for single and double sided POOL-CO markets are considered. The strategic bidding in both single and double sided POOL-CO markets are done by ISO based on uniform MCP. Moreover, an Oppositional Gravitational Search Algorithm (OGSA) has been implemented in order to optimize the single hour trading period bids in single-sided POOL-CO market to maximize the individual GENCO profit. Meanwhile, the ramp rate limits are considered for multi-hour trading period and optimized bids are obtained using OGSA. Moreover, in order to deal with GENCO's profit maximization issue, the information of opponent bid is solved utilizing joint normal probability distribution function. Notably, the profit of each power supplier can be maximized if the optimized bids are submitted to ISO and the participation of generators in a day ahead electricity market bidding process without considering ramp rate limits will cause economic loss to the generators as this extra cost is beared by generators. Further, double-sided bidding strategy is formulated as multi objective with the objective of social welfare maximization. A Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) along with OGSA has been implemented in order to optimize the single hour trading period bids in double-sided POOL-CO market to maximize the profits of the individual's power supplier and large buyer. A standard IEEE 30-bus with two large consumers is considered in single hour trading period. Moreover, in order to deal with large consumers profit maximization issue, the information of opponent bid is solved utilizing joint normal probability distribution function. It is found that, proposed TOGSA increases the trading of power between suppliers and buyers, and also maximize the social welfare.
The single and double sided bidding strategies with amalgamation of renewable (such as

wind and solar) energy sources participating in single hour trading period are proposed. Wind and solar are used as probabilistic manner to model the uncertainty and their prediction error are considered in cost function using underestimation and overestimation. Furthermore, the uncertainty of the behaviour of rival is minimized using the function of normal distribution of probability. The uniform MCPs in both types of bidding model with the presence of renewable energy sources are calculated. The proposed bidding strategies are analytically tested on standard IEEE 30 and 57 bus systems respectively. It is found that, incorporating wind and solar power also affects the bid as it reduces the CPS generation and provides less MCP value that would deliver sufficient electricity from accepted sales bids to meet all accepted purchase bids and increase the total traded power. Further, it is also found that, the overestimation of uncertainty is very less as compared to the underestimation in both the solar and wind power generation. This will encourage the solar and wind power suppliers for bidding the extra power into the real-time market if the underestimation is positive.
A suitable bidding strategy is indispensable for power suppliers in the energy and reserve services market is considered. The uniform MCPs in both markets are calculated. Furthermore, the uncertainties of the behaviour of rival in both markets are minimized using the function of normal distribution of probability. The coordinated bidding strategy for profit maximization of competitive power suppliers in an energy and reserve market has been solved using OGSA. The proposed algorithm was tested on 6 supplier system considering 1 supplier as main generator and other 5 as its rival generators. The results indicate the increase in profit of the main generator and it's MCP in both markets.

1.7 Outline of The Thesis

This thesis is divided into 6 Chapters. Chapter 1 discusses the hierarchy, structure, and functioning of electricity markets and provides an insight into the state-of-the-art optimal bidding strategies in an emerging electricity market. A detailed literature survey focused on the existing bidding strategies such as single side for profit maximization of power suppliers, double side for profit maximization of power suppliers and large buyers, bidding strategies for renewable power suppliers, and coordination of bidding strategies in day-ahead energy and reserve markets for profit maximization of power suppliers has been presented. Moreover, the detailed literature survey also focused on existing solution methods of bidding strategies, along with the limitations of these existing methods, has been presented. On the basis of literature survey, the research objectives have been formulated. Additionally, the major contributions of the thesis work have been included in this Chapter.

In Chapter 2, optimization techniques such as Oppositional Gravitational Search Algorithm (OGSA) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) along with OGSA (TOGSA) to solve different strategic bidding problems has been discussed.

In Chapter 3, presented single side bidding strategy for profit maximization of power suppliers participating in a single hour and multi-hour trading period and double side bidding strategy for profit maximization of power suppliers and large buyers participating in a single hour trading period.

In Chapter 4, optimum bidding strategies such as single-side for power supplier and double side for power suppliers and large buyers have been formulated with amalgamation of substantial wind and solar based power generation. Moreover, the wind and solar are used as probabilistic manner to model the uncertainty and their prediction error are considered in cost function using underestimation and overestimation.

In Chapter 5, optimal coordinated bidding strategy between energy and reserve markets is considered for six generating units system considering 1 supplier as main generator and other 5 as its rival generators. The considered framework is utilized to obtain the maximum profit for power suppliers.

In Chapter 6, conclusions and future scope of the proposed research work are discussed.

Chapter 2

Optimization Techniques to Solve Strategic Bidding Problems

2.1 Introduction

Problems involving global optimization throughout the scientific community are omnipresent. In fields such as engineering, statistics and finance, global optimization is needed. But numerous practical problems have non-linear, non-continuous, non-differentiable, noisy, multi-dimensional, flat, constraints or stochastic functions. Such problems are challenging and cannot be analytically solved. The standard method to an optimization issue starts with the design of an objective function that can shape the goals of the problem while incorporating any limitations. The standard methods of optimization are linear programming, dynamic programming, gradient search and other related methods. These standard methods have difficulty dealing with the complexities of problems in the real world. Users usually require three requirements to be met by a practical optimization technique. Firstly, the method should find the global solution irrespective of the parameter values of the initial system. Secondly, there should be rapid convergence. Third, a minimum number of control parameters should be available to the program to make it easy to handle. Oppositional Gravitational Search Algorithm (OGSA) and a Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) along with OGSA can fulfill all above mentioned requirements. Therefore, they are used to solve problems in the real world.

2.2 Oppositional Gravitational Search Algorithm (OGSA)

Gravitational Search Algorithm (GSA) [73] implementation for power system problems provides high-quality results [74–78] as this algorithm have the best tunable parameters. Its most extensive feature is an adjustment of gravitational constant for improvement of the search accuracy. It provides a fast solution with high-quality results [79]. In GSA technique, the initialization of population is configured randomly, and the activity approach of different parameters is dependent on randomness. If the random guess is not far away from the optimal result, convergence can be achieved quickly. However, on the contrary the random guess may be far away from the optimal result. This pessimistic scenario will lead to an additional wastage of time while searching for optimal solution or in worst case may end up resulting in non-optimal solution. In fact it is impossible to make a best initial guess without having any previous knowledge about the situation. Therefore, logically we should be looking for all possible options or more precisely we must look in the opposite direction also. Considering this fact, in GSA, oppositional population based learning (OBL) concept [80] is incorporated. The utilization of opposite agents in the evaluation process of GSA enables enhanced exploration of the search space. This prevents trapping of the search in local optimal solution. A step-by-step procedure of OGSA to solve the problem of optimization is as follows:

1. Initialization of Population: Assume a system consist of N agents (masses), position of the y^{th} agent is represented by:

$$\lambda_y = (\lambda_y^1, ..., \lambda_y^D, ..., \lambda_y^M) \tag{2.1}$$

   where, $\lambda_y^D \in [L_y^D, U_y^D]$ is the y^{th} agent position in the D^{th} dimension and M is the dimension of search space and L_y^D, U_y^D are lower bound and upper bound limits of y^{th} agents in the D^{th} dimension.

2. Opposition phenomenon in GSA: In [80], authors have presented opposition based learning phenomenon. In that work, the authors have considered the current and opposite agents in order to get a better estimation of current agent result. It is concluded that an opposite agent provides better optimal solutions compared to that of random agent solutions. The opposite agents positions $(O\lambda_y)$ are completely defined by components of λ_y

$$O\lambda_y = [O\lambda_y^1, ..., O\lambda_y^D, ..., O\lambda_y^M] \tag{2.2}$$

where, $O\lambda_y^D = L_y^D + U_y^D - \lambda_y^D$ with $O\lambda_y^D \in [L_y^D, U_y^D]$ is the position of y^{th} opposite agent $O\lambda_y$ in the D^{th} dimension of oppositional population.

3. At the OGSA starting an iterative process, a joint population of $\{\lambda, O\lambda\}$ is generated with all the constraint is satisfied. Selection strategies are used to select the N number of fittest agents from the joint population set of $\{\lambda, O\lambda\}$ generated current population λ as follow:

$$\lambda_y(i) = \begin{cases} O\lambda_y(i) \quad if \quad fit(O\lambda_y(i) > fit(\lambda_y(i)) \\ \lambda_y(i) \quad otherwise \end{cases} \tag{2.3}$$

The algorithm simultaneously evaluates the fitness of an agent and its opposite agent. The agent with better fitness value is used in further computation and the other agent is discarded.

4. Acceleration of agents: The fitness evaluation is used to calculate the mass of each agent in GSA. The mass of each agent is calculated as follows:

$$M_y(i) = \frac{m_y(i)}{\sum\limits_{l=1}^{N} m_l(i)} \tag{2.4}$$

here, $m_y(i) = \frac{fit_y(i) - worst(i)}{best(i) - worst(i)}$
where $M_y(i)$ is the normalized mass of y^{th} agent at i^{th} iteration and $worst(i)$, $best(i)$ are the worst and best fitness of all agents at i^{th} iteration.
The acceleration $a_y^D(i)$ acting on y^{th} agent at i^{th} iteration is evaluated follows:

$$a_y^D(i) = \sum_{\substack{l \in Gbest, \\ l \neq y}} rand_l \quad G(i) \frac{M_y(i)}{R_{yl}(i) + E} (\lambda_l^D(i) - \lambda_l^D(i)) \tag{2.5}$$

where set of first 2% agents are G_{best} with best value of fitness and greatest mass $rand_l$ is the uniform random number between interval $(0, 1)$. $R_{yl}(i)$ is the Euclidean distance between two agents y^{th} and l^{th} at i^{th} iteration and E is a small positive constant. The gravitational function $G(i)$ is represented by

$$G(i) = G \times \left(1 - \frac{iteration}{Total \quad iteration} \right) \tag{2.6}$$

here, $G = c \max\limits_{D \in \{1,2,.....,M\}} \left(|\lambda_U^D - \lambda_L^D| \right)$ where c is search interval parameter

5. Update the position and agents velocity: In next $(i+1)^{th}$ iteration, the position and agents velocity is calculated as follows

$$\begin{cases} v_y^D(i+1) = rand_y \times v_y^D(i) + a_y^D(i) \\ \lambda_y^D(i+1) = \lambda_y^D(i) + v_y^D(i+1) \end{cases} \tag{2.7}$$

where $rand_y$ is a random number between interval (0, 1), $v_y^D(i)$ is the velocity of y^{th} agent at D^{th} dimension during i^{th} iteration and $\lambda_y^D(i)$ is the position of y^{th} agent at D^{th} dimension during i^{th} iteration.

2.3 Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

Recently, TOPSIS has been introduced in [81–85] for providing uniformly distributed Pareto front of multi-objective problems. The approach applies Euclidean geometry to offer uniform distribution of result for multi-objective optimization problems as compared to available methods. In this method, Euclidean distances of individual solutions are minimized from its excellent set of solutions; known as Positive Ideal Solution (PIS), while simultaneously maximizing the distances from worst set of solutions, known as Negative Ideal Solution (NIS). This method can be combined with any recent heuristic optimization method to choose the best compromising result at some point of iterations of technique.

2.3.1 Multi-objective Problem Formulation using TOPSIS Technique

All objectives of the problem can be represented as
Maximize

$$[O_1(x), \mathrm{O}_2(x), ..., O_{n_2}(x)] \tag{2.8}$$

Subject to $x \in S$

where, $O_i(x) : R^n \rightarrow R$ is i^{th} objective, $i = 1, 2, ..., n2$, $n2 > 1$, and S is space of the search.
As mentioned, TOPSIS technique is implemented to frame and solve the multi-objective double sided strategic bidding problem for profit maximization of the suppliers and large buyers. In this technique, Euclidean geometry is applied, and two reference points like PIS

and NIS are used to find best compromising result. Therefore, choice of the alternative result should be at nearest Euclidean distance from PIS and farthest from NIS. Using this procedure, the solutions remain concentrated around their individual best solution. This enables higher quality of results for actual multi-objective optimization problems. In TOPSIS technique following steps are used to solve multi-objective problems:

1. Frame a standardized selection matrix to transform all dimensional functions in to non-dimensional functions. The factors of matrix may be represented by

$$F_{ab} = \frac{O_{ab}}{\sqrt{\sum_{a=1}^{n_1} O_{ab}^2}} \qquad \forall \quad \mathrm{a} \in \mathrm{n}_1 \quad \& \quad \mathrm{b} \in \mathrm{n}_2 \tag{2.9}$$

   where, n_1 is the number of elements and O_{ab} is the value of a^{th} element of b^{th} objective.

2. A weighted standardized selection matrix may be built to offer weights to the objects if required. The step can avoid if all objects are similarly significant. The factors of the matrix are represented by

$$W_{ab} = w_b \times F_{ab} \qquad \forall \quad \mathrm{a} \in \mathrm{n}_1 \quad \& \quad \mathrm{b} \in \mathrm{n}_2 \tag{2.10}$$

   where, w_b is weight of the b^{th} objective and $\sum_{b=1}^{n_2} w_b = 1$.

3. To maintain the best and worst solutions of the each objective, PIS and NIS are calculated and expressed as:

$$PIS = \left\{W_1^+, W_2^+, W_3^+, ..., W_{n2}^+\right\} \tag{2.11}$$

$$NIS = \left\{W_1^-, W_2^-, W_3^-, ..., W_{n2}^-\right\} \tag{2.12}$$

   where, $W_b^+ = \begin{cases} \max \langle W_{ab} \rangle & \forall \text{ a; if object denotes a profit} \\ \min \langle W_{ab} \rangle & \forall \text{ a; if object denotes a benefit} \end{cases}$

   $W_b^- = \begin{cases} \max \langle W_{ab} \rangle & \forall \text{ a; if object denotes a benefit} \\ \min \langle W_{ab} \rangle & \forall \text{ a; if object denotes a profit} \end{cases}$

4. For every opportunity from PIS and NIS, Euclidean distances d_{b+} and d_{b-} are measured and given by:

$$d_b^+ = \sqrt{\sum_{b=1}^{n2} \left(W_{ab} - W_b^+\right)^2} \quad \& \quad d_b^- = \sqrt{\sum_{b=1}^{n2} \left(W_{ab} - W_b^-\right)^2} \tag{2.13}$$

5. The Relative Closeness Index (RCI) can be measured for individual opportunity using the value from Step 4.

$$RCI_a^+ = \frac{d_a^+}{d_a^+ + d_a^-} \tag{2.14}$$

The best compromising results may be selected from RCI. Whose alternatives have highest RCI value will be selected as the best compromising result.

2.4 Conclusion

Several techniques of heuristic optimization have been introduced in recent years. Some of these techniques are inherently inspired by swarm behaviors. A modified optimization technique is introduced in this Chapter, which is called OGSA. OGSA is based on opposition learning phenomenon. This technique considers both the current and the opposite agent position in order to obtain better estimate of agent position. The opposition operator in OGSA helps to provide search space, where the GSA fails to reach. It helps to avoid the search to get trapped at local optimal solution.
To obtain the most compromising solution for contradictory multi-objectives optimization problem, recently, TOPSIS along with OGSA (TOGSA) has been also introduced in this Chapter. This method extends Euclidean geometry to give for multi-objective optimization problems a uniform distribution of results. This technique minimizes Euclidean distances from its outstanding set of alternatives ; known as PIS, while maximizing distances from the worst set of alternatives, known as NIS.

In the next Chapter, the optimal bidding strategies in single side and double side trading mechanisms have been investigated using proposed OGSA and TOGSA respectively for maximization of the profit for market participants. In addition, the performances of the proposed techniques have been compared with the existing results based on available different methods in the literature.

Chapter 3

Bidding Strategies for Electricity Market Participants

3.1 Introduction

The bidding strategies employed by different market participants in an emerging power market environment have substantial influences on their profits/benefits and a power market's operating behavior. The power market is continuously growing after deregulation in electricity market structures since 1980 and introduces competition among all entities in energy market. Moreover, unbundling of vertically integrated electricity market creates open access environment for network access which encourages the development of new technologies to build a competitive electricity market to improve its performance [5]. But the unexpected changes in electricity market introduce imperfection in the market. In microeconomics theory, market participants take advantage of imperfections to increase profits through bidding in the market. Theoretically, they maximize their benefits through bidding a price equal to their expenses of their marginal seller and buyer cost. But practically, they have higher bidding prices over their marginal selling and buying cost [2]. Power market structure is essential to accommodate market entities in the system for making power transactions. Various models have been developed based on trading strategy and number of participants to ensure secure and economical operation. Among all the classical models discussed in the scientific literature, power POOL-CO model is extensively utilized for centralized trading between buyers and sellers. In this model, sellers and buyers of electricity typically submit the sealed bids to the pool for the amounts of power they are willing to trade in the electricity market. However, due to the limitation of sealed bids, the sellers and buyers are found to be facing problems such as uncertain behavior of rivals. These problems are known as a strategic bidding problem [9, 10]. In this sense, sellers and buyers can exercise strategic bidding to achieve the maximum profit. Therefore in this chapter, optimum bidding strategies such as single sided for power supplier and double sided for power suppliers and large buyers have been formulated to achieve the maximum profit of power supplier and large buyer.

3.2 Market Clearing Mechanism in a POOL Based Energy Market

The market participants submit their bids to the central POOL-CO mechanism market structure. There are two type of central POOL-CO bidding mechanisms namely; single-sided market structure and double-sided market structure, which are taken into account in this chapter. Single-sided bidding POOL-CO mechanism allows only power suppliers to participate in the energy markets. They can submit their energy supply bids to the PX-managed energy market whereas, the system operator manages the transmission facilities. The ISO controls the system operator, PX, and receives bids of energy from power suppliers. After that the generation outputs sets are calculated to meet the requirement of demand. In the double side bidding mechanism, both suppliers and large buyers are permitted to submit their bids to the central pool [6]. In this mechanism ISO receives electricity transaction bids from power suppliers as well as large buyers and economically dispatch them based on their price and MW bids. These operations are carried out in indirect ways which is governed by the pool operator. Both power suppliers and large buyers send their bids to the ISO, and then ISO determines the bids based on the MCP as a sole decision maker. There are various ways to define MCP in the central POOL type market. In this context, the most common method is the uniform price method where the point of market equilibrium occurs at the intersection of the supply and demand incremental cost curve [86]. It is noteworthy that both power suppliers and large buyers optimize their bidding data with the objective of their peculiar profit maximization before submitting bids to the pool operator and then provide the optimized proposals to the ISO. Further, it can also estimate the bidding value of the rival by using the joint normal Probability Distribution Function (PDF) [11].

3.2.1 Single-sided POOL Based Energy Market

In a single-sided POOL based energy market, each PS is required to submit a bid as a non-decreasing linear supply function to the POOL [11]. The linear non-decreasing supply bid function of the m^{th} power supplier can be represented as

$$\alpha_{m,t} + \beta_{m,t} PG_{s,m,t} = R_{s,t} \tag{3.1}$$

The linear non-decreasing supply bid function given in equation (3.1) includes different constraints such as

1. Power balance constraints: The constraint of the power balance is a constraint of equality that reduces the power system to a fundamental principle of equilibrium between the total generation of GENCO participating in the electricity markets and the customers' demand profile.

$$\sum_{m=1,t=1}^{PS,T} PG_{s,m,t} = D\left(R_{s,t}\right) \tag{3.2}$$

2. Forecasted demand constraints: It is said that the demand for electricity is elastic if a change in price percentage demand results in a larger change in demand percentage. On the other hand, the demand is said to be inelastic if the relative change in demand is lower than the relative price change. The forecasted demand can be calculated as

$$D\left(R_{s,t}\right) = D_{c,t} - K \times R_{s,t} \tag{3.3}$$

3. Maximum and minimum power generation limits of the power generators: The power generation units have maximum and minimum limits of production directly associated with the design of the generator, which can be defined as a pair of constraints on inequality.

$$PG_{\min,s,m,t} \leq PG_{s,m,t} \leq PG_{\max,s,m,t} \tag{3.4}$$

4. Up and down Ramp rate limits of the power generators: The rate of up and down of the generators power output is kept within scale so as to maintain thermal gradients within secure limits and to obstruct decline in lifespan of the turbine. These constraints of ramp rate can be expressed as

$$-RD_m \leq \left(PG_{s,m,t} - PG_{s,m,t-1}\right) \leq RU_m \tag{3.5}$$

After receiving the supplier's bid, pool decided the output of active power generation and meets with the total system demand and then minimizes total buying cost. It noted that equations (3.1)-(3.4) should satisfy the power dispatch when considering power balance constraint (3.2) and power inequality constraints (3.4). Generally, the MCP is decided in such a way that the supply bids and demand bids are aggregated respectively into a supply curve and demand curve. The supply curve and demand curve intersection point is the MCP. For the MCP calculation (3.1)-(3.3) has been taken into consideration while (3.4) and (3.5) are neglected and can be expressed as

$$R_{s,t} = \frac{D_{c,t} + \sum\limits_{m=1,t=1}^{PS,T} \frac{\alpha_{m,t}}{\beta_{m,t}}}{K + \sum\limits_{m=1,t=1}^{PS,T} \frac{1}{\beta_{m,t}}} \tag{3.6}$$

Each power supplier can calculate the power dispatch as

$$PG_{s,m,t} = \frac{R_{s,t} - \alpha_{m,t}}{\beta_{m,t}} \tag{3.7}$$

For each supplier minimum and maximum generation limits are taken into account while dispatching power. In order to participate in the market competition each supplier must be able to provide preset minimum power requirement. However, if the supplier violates the maximum generation limit then equation (3.4) will decide its upper limit.

3.2.2 Double-sided POOL Based Energy Market

In a double-sided POOL based energy market, each PS and large buyer is required to submit a bid as a linear non-decreasing supply and non-increasing demand bid functions to the POOL [32]. The linear non-decreasing supply bid function of the m^{th} power supplier and the linear non-increasing demand bid function of the n^{th} large buyer can be represented respectively as

$$\alpha_{m,t} + \beta_{m,t} PG_{d,m,t} = R_{d,t} \tag{3.8}$$

$$\phi_{n,t} - \varphi_{n,t} CD_{n,t} = R_{d,t} \tag{3.9}$$

The linear non-decreasing supply and non-increasing demand bid function given in equations (3.8) and (3.9) respectively, which includes different constraints such as

1. Power balance constraints: The constraint of the power balance is a constraint of equality that reduces the power system to a fundamental principle of equilibrium between the total generation of GENCO and total demand profile of customers participating in the electricity markets.

$$\sum_{m=1,t=1}^{PS,T} PG_{d,m,t} = D\left(R_{d,t}\right) + \sum_{n=1,t=1}^{LB,T} CD_{n,t} \tag{3.10}$$

2. Forecasted demand constraints: The forecasted demand is claculated in similar way of equation (3.3) and can be represented as

$$D\left(R_{d,t}\right) = D_{c,t} - K \times R_{d,t} \tag{3.11}$$

3. Power suppliers and large buyers bid limits constraints: The power suppliers bid limits can be incorporated in the same way as equation (3.4) while large buyers bid limits can be set as follows:

$$PG_{\min,d,m,t} \leq PG_{d,m,t} \leq PG_{\max,d,m,t} \tag{3.12}$$

$$CD_{\min,n,t} \leq CD_{n,t} \leq CD_{\max,n,t} \tag{3.13}$$

After receiving the supplier's and large buyer's bid, pool decided the output of active power generation and meets with the total system demand to minimize total buying cost and maximizing social welfare. As explained in Section (2), similar procedure has been used for MCP calculation. In this section, (3.8), (3.9), (3.10) and (3.11) has been employed to calculate MCP whereas (3.12) and (3.13) are avoided. Mathematically it can be expressed as

$$R_{d,t} = \frac{D_{c,t} + \sum\limits_{m=1,t=1}^{PS,T} \frac{\alpha_{m,t}}{\beta_{m,t}} + \sum\limits_{n=1,t=1}^{LB,T} \frac{\phi_{m,t}}{\varphi_{m,t}}}{K + \sum\limits_{m=1,t=1}^{PS,T} \frac{1}{\beta_{m,t}} + \sum\limits_{n=1,t=1}^{LB,T} \frac{1}{\varphi_{n,t}}} \tag{3.14}$$

Each power supplier can calculate the power dispatch and each large buyer can calculate the demand respectively as

$$PG_{d,m,t} = \frac{R_{d,t} - \alpha_{m,t}}{\beta_{m,t}} \tag{3.15}$$

$$CD_{n,t} = \frac{\phi_{n,t} - R_{d,t}}{\varphi_{n,t}} \tag{3.16}$$

For each power supplier and large buyer minimum and maximum generation and demand limits are taken into account while dispatching power. If the power supplier and large buyer violates the generation and demand limit, then equation (3.12) and (3.13) will decide its limit respectively.

3.3 Problem Formulation in Single Side POOL Based Energy Market

In a single side POOL based energy market, only power suppliers participate in bidding process. The aim of profit maximization of the power suppliers participating in single side POOL based energy market and competing with other suppliers can be set as
Maximize

$$\text{Profit} = \text{Revenue} - \text{Production} \quad \text{Cost} \tag{3.17}$$

Revenue: Total energy sales are referred to as revenue of power supplier. It is calculated by multiplying MCP with power dispatch. It can be represented as

$$Revenue = R_{s,t} \times PG_{s,m,t} \tag{3.18}$$

Production Cost: The production cost function of the power supplier is approximated as a quadratic function which can be represented as

$$PC_{s,m,t}(PG_{s,m,t}) = a_{m,t}PG_{s,m,t} + b_{m,t}PG^2_{s,m,t} \tag{3.19}$$

Substitute equations (3.18) and (3.19) in to the equation (3.17). Now the modified equation can be presented as
Maximize

$$F_s(\alpha_{m,t}, \beta_{m,t}) = R_{s,t} \times PG_{s,m,t} - PC_{s,m,t}(PG_{s,m,t}) \tag{3.20}$$

Subject to: Power balance constraints as given in equation (3.2) and power inequality constraints as given in equations (3.4) and (3.5)

3.4 Problem Formulation in Double Side POOL Based Energy Market

In a double side POOL based energy market, both power suppliers and large buyers will participated in bidding process. The aims of profit and benefit maximization of the power suppliers and large buyers are participating in energy markets and competing with other suppliers and buyers. Similar procedure as explained in Section 3 is utilized for calculation of power supplier profit and can be represented as
Maximize

$$F_d(\alpha_{m,t}, \beta_{m,t}) = R_{d,t} \times PG_{d,m,t} - PC_{d,m,t}(PG_{d,m,t}) \tag{3.21}$$

Large buyer benefit function is given as
Maximize

$$\text{Benefit} = \text{Purchasing} \quad \text{Cost} - \text{Buyer} \quad \text{Revenue} \tag{3.22}$$

Purchasing Cost: The large buyers purchasing cost function can be represents as

$$PC_{d,n,t}(CD_{n,t}) = e_{n,t}CD_{n,t} - f_{n,t}CD^2_{n,t} \tag{3.23}$$

Buyer Revenue: Large buyer revenue can be expressed as

$$Buyer \quad Revenue = R_{d,t} \times CD_{n,t} \tag{3.24}$$

Substitute equations (3.23) and (3.24) in to the equation (3.22). Now modified equation can be represented as

$$F_d(\phi_{n,t}, \varphi_{n,t}) = PC_{d,n,t}(CD_{n,t}) - R_{d,t} \times CD_{n,t} \tag{3.25}$$

Subject to equations (3.10) , (3.12) and (3.13)
In the literature, rivals bidding behaviors are represented as a discrete probability distribution function to the solution of strategic bidding model. The objective functions depicted in (3.20), (3.21) and (3.25) subject to the given constraints. These objective functions are behaving as non-linear functions with unknown stochastic constraints. To solve this non linear problem heuristic approach is considered over classical methods.
Bidding data of participants in both type of sealed bidding model for next duration is confidential. Therefore, participants do not have information about other participant's bid. However, last duration bidding data information is available, based on this data, estimation of MCP is possible. Each participant tries to estimate other participants bidding

coefficients, but this is difficult. So from participant's point of view, the bidding coefficient follows a normal joint PDF.

3.5 Joint Normal Probability Distribution Function

Each power supplier bidding coefficients $\alpha_{m,t}$ and $\beta_{m,t}$ follow the normal joint distribution with the following PDF [32] where rivals m^{th} (m not equal to i) in both type of POOL based energy market.

$$\mathrm{pdf}_{i,t}(\alpha_{m,t},\beta_{\mathrm{m,t}}) = -\frac{1}{2\pi\sigma_{m,t}{}^{(\alpha)}\sigma_{\mathrm{m,t}}{}^{(\beta)}\sqrt{1-\rho_{\mathrm{m,t}}^2}}\times\exp\left\{-\frac{1}{2\left(1-\rho_{\mathrm{m,t}}^2\right)}\left[\left(\frac{\alpha_{\mathrm{m,t}}-\mu_{\mathrm{m,t}}^{(\alpha)}}{\sigma_{\mathrm{m,t}}^{(\alpha)}}\right)^2+\left(\frac{\beta_{m,t}-\mu_{\mathrm{m,t}}^{(\beta)}}{\sigma_{m,t}^{(\beta)}}\right)-\frac{2\rho_{\mathrm{m,t}}\left(\alpha_{\mathrm{m,t}}-\mu_{\mathrm{m,t}}^{(\alpha)}\right)\left(\beta_{\mathrm{m,t}}-\mu_{\mathrm{m,t}}^{(\beta)}\right)}{\sigma_{\mathrm{m,t}}^{(\alpha)}\sigma_{\mathrm{m,t}}^{(\beta)}}\right]\right\} \tag{3.26}$$

This PDF can be indicated in the compressed form as

$$(\alpha_{m,t},\beta_{m,t})_i \sim N\left\{\begin{bmatrix}\mu_{m,t}^{(\alpha)}\\ \mu_{m,t}^{(\beta)}\end{bmatrix},\begin{bmatrix}\left(\sigma_{m,t}^{(\alpha)}\right)^2 & \rho_{m,t}\sigma_{m,t}^{(\alpha)}\sigma_{m,t}^{(\beta)}\\ \rho_{m,t}\sigma_{m,t}^{(\alpha)}\sigma_{m,t}^{(\beta)} & \left(\sigma_{m,t}^{(\beta)}\right)^2\end{bmatrix}\right\} \tag{3.27}$$

The marginal distributions of $\alpha_{m,t}$ and $\beta_{m,t}$ are both normal with mean values of $\mu_{m,t}^{(\alpha)}$ and $\mu_{m}^{(\beta)}$, and standard deviations $\sigma_{m,t}^{(\alpha)}$ and $\sigma_{m,t}^{(\beta)}$ respectively. Similarly, each large buyer bidding coefficients $\phi_{n,t}$ and $\varphi_{n,t}$ follow the normal joint distribution with the following PDF with n^{th} rivals.

$$(\phi_{n,t},\varphi_{n,t})_j \sim N\left\{\begin{bmatrix}\mu_{n,t}^{(\phi)}\\ \mu_{n,t}^{(\varphi)}\end{bmatrix},\begin{bmatrix}\left(\sigma_{n,t}^{(\phi)}\right)^2 & \rho_{n,t}\sigma_{n,t}^{(\phi)}\sigma_{n,t}^{(\varphi)}\\ \rho_{n,t}\sigma_{n,t}^{(\phi)}\sigma_{n,t}^{(\varphi)} & \left(\sigma_{n,t}^{(\varphi)}\right)^2\end{bmatrix}\right\} \tag{3.28}$$

3.5.1 Calculation of Joint Normal Probability Distribution Function Parameters

The approximation of parameters in joint PDF for the i^{th} power suppliers [11] and j^{th} large buyer [32] in energy market are calculated according to bidding data of previous hour.

Power supplier joint PDF parameters are estimated as follows

$$\begin{aligned}&\mu_{m,t}^{\alpha} = 1.2\times a_{m,t} \qquad \mu_{m,t}^{\beta} = 1.2\times b_{m,t} \qquad \rho_{m,t} = -0.1\\ &4\sigma_{m,t}^{\alpha} = 0.15\times a_{m,t} \Rightarrow \sigma_{m,t}^{\alpha} = 0.15\times a_{m,t}/4\\ &4\sigma_{m,t}^{\beta} = 0.15\times b_{m,t} \Rightarrow \sigma_{m,t}^{\beta} = 0.15\times b_{m,t}/4\end{aligned} \tag{3.29}$$

Large buyer joint PDF parameters are estimated as

$$
\begin{aligned}
&\mu^{\phi}_{n,t} = 0.8 \times e_{n,t} \qquad \mu^{\varphi}_{n,t} = 1.2 \times f_{n,t} \qquad \rho_{n,t} = 0.1 \\
&4\sigma^{\phi}_{n,t} = 0.2 \times e_{n,t} \Rightarrow \sigma^{\phi}_{n,t} = 0.2 \times e_{n,t}/4 \\
&4\sigma^{\varphi}_{n,t} = 0.15 \times f_{n,t} \Rightarrow \sigma^{\varphi}_{n,t} = 0.2 \times f_{n,t}/4
\end{aligned}
\tag{3.30}
$$

The aforementioned assumption in (3.29) for parameters of joint PDF is in accordance with the bidding strategy of suppliers. The supplier is very likely to bid above production cost because it is known that in an oligopoly market, suppliers have some market power. Therefore, the expected values of $\alpha_{m,t}$ and $\beta_{m,t}$, i.e., $\mu^{(\alpha)}_{m,t}$ and $\mu^{(\beta)}_{m}$ are assumed to be 20% [11] above $a_{m,t}$ and $b_{m,t}$ respectively. The Standard Deviation of $\alpha_{m,t}$ and $\beta_{m,t}$ are assumed as $\sigma^{(\alpha)}_{m,t}$ and $\sigma^{(\beta)}_{m,t}$ such that $a_{m,t}$ and $b_{m,t}$ fall in range of $\left[\mu^{\alpha}_{m,t} - 4 \times \sigma^{\alpha}_{m,t}, \mu^{\alpha}_{m,t} + 4 \times \sigma^{\alpha}_{m,t} = 1.05 \times a_{m,t}, 1.35 \times a_{m,t}\right]$ and $\left[\mu^{\beta}_{m,t} - 4 \times \sigma^{\beta}_{m,t}, \mu^{\beta}_{m,t} + 4 \times \sigma^{\beta}_{m,t} = 1.05 \times b_{m,t}, 1.35 \times b_{m,t}\right]$ respectively with probability 0.999. It is assumed that $\rho_{m,t} < 0$, to mimic the response of bidding coefficients. For example, if supplier increase any of the coefficient, it will most likely result in decrements of other coefficient. This is because supplier does not expect higher bid price fluctuations to escape the risk of not being dispatch. So, the above stated assumptions are in accordance to suppliers with market power. The same explanation applies to the aforementioned assumption in (3.30) for parameters of joint pdf in accordance with the bidding strategy of buyers. In literature, rivals' bidding behaviors are represented as a discrete probability distribution function to the solution of strategic bidding model. Therefore, depending on the bidding models, objective function and constraints may not be differentiable. In that case conventional methods cannot be applied, whereas, heuristic and metaheuristic methods could be applied.

In the process of strategic bidding, the coefficients of bidding are not considered individually for maximization of profit of market entities. Due to the inter-dependency of bidding coefficients, the values of one bidding coefficient is considered as known values and other bidding coefficient are determined by using an optimization method [11]. The proposed OGSA and TOGSA are respectively applied to solve the above stochastic single and double side optimization problem. The bid data of the rivals and their corresponding joint normal PDFs are estimated in MATLAB using the commands 'mvnrnd' and 'mvnpdf' respectively and then given as the OGSA and TOGSA input.

3.6 Solution Methodology

3.6.1 Solution Procedure of OGSA Applied to Single Side Optimal Bidding Strategy Problem

1. Set input data of considered test system for single side bidding strategy and parameters of the proposed OGSA.

2. Set population size (N) and randomly generate initial population λ for bidding coefficient $\beta_{m,t}$ of power suppliers in the decided search space of the problem.

3. Determine the market clearing price as (3.6) and dispatch of each generator as (3.7).

4. Set power generation limits as (3.4) and system load balance as (3.2) then calculate profit of each power supplier as (3.20).

5. Generate opposite population ($O\lambda$) to the initial generated population (λ) in search space. Then determine the market clearing price as (3.6) and dispatch of each generator as (3.7).

6. Set power generation limits as (3.4) and system load balance as (3.2) then calculate profit of each power supplier as (3.20).

7. Evaluate the fitness function for all random (λ) and opposite ($O\lambda$) population.

8. Select N fittest agents from current (λ) and opposite population ($O\lambda$) as current population (λ).

9. Determine the mass of every agent as (2.4) and gravitational constant as (2.6) respectively.

10. Calculate all agents' acceleration as (2.5).

11. Update respectively the velocity and the position of the agent as (2.7).

12. If the maximum number of iterations are not exceeded go to Step 3. Otherwise the procedure will be stopped and the optimum single side bidding strategy printed.

The solution approach in single side bidding mechanism using OGSA is given as a flowchart in Figure 3.1.

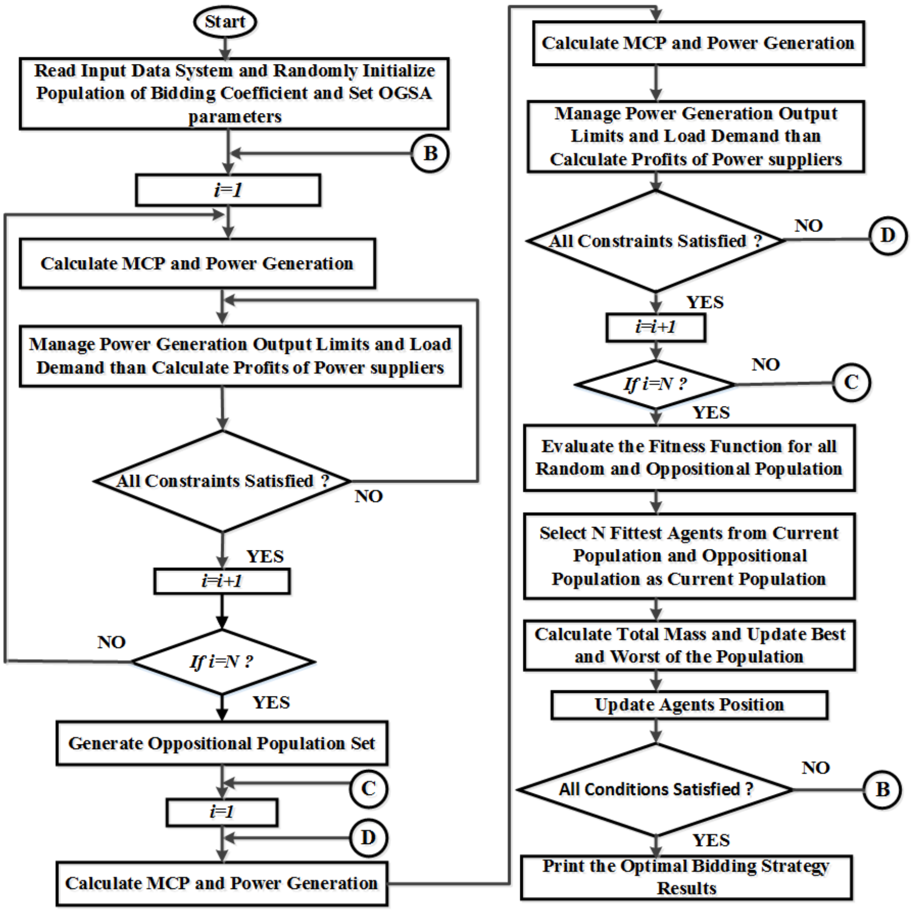


FIGURE 3.1: Solution approach as a flowchart using OGSA

3.6.2 Solution Procedure of TOGSA Applied to Double Side Optimal Bidding Strategy Problem

1. Set input data of considered test system for double side bidding strategy and parameters of the proposed TOGSA.

2. Set population size (N) and randomly generate initial population λ for bidding coefficient $\beta_{m,t}$ of power suppliers in the decided search space of the problem.

3. Determine the market clearing price as (3.14), dispatch of each generator as (3.15) and demand of each large buyer as (3.16).

4. Set power generation limits as (3.12), demand limits as (3.13) and system load balance as (3.10) then calculate profit of each power supplier as (3.21) and benefit of each buyer as (3.25).

5. Generate opposite population ($O\lambda$) to the initial generated population (λ) in search space. Then determine the market clearing price as (3.14), dispatch of each generator as (3.15) and demand of each large buyer as (3.16).

6. Set power generation limits as (3.12), demand limits as (3.13) and system load balance as (3.10) then calculate profit of each power supplier as (3.21) and benefit of each buyer as (3.25).

7. Add the solution of (3.21) and (3.25) for all random (λ) and opposite ($O\lambda$) population respectively as $0.5 * [(3.21) + (3.25)]$.

8. Evaluate the solution of (3.21) and (3.25) for all random (λ) and opposite ($O\lambda$) population.

9. Select N fittest agents from current (λ) and opposite population ($O\lambda$) as current population (λ).

10. Construct a decision matrix as (2.9).

11. Apply TOPSIS approach to select the best solution of (3.21) and (3.25) with high RCI value according to (2.14) as fitness function and corresponding fittest agents.

12. Determine the mass of every agent as (2.4) and gravitational constant as (2.6) respectively.

13. Calculate all agents' acceleration as (2.5).

14. Update the respective velocity and position of the agent as (2.7).

15. If the maximum number of iterations are not exceeded go to Step 3. Otherwise the procedure will be stopped and the optimum double side bidding strategy printed.

The solution approach in double side bidding mechanism using TOGSA is given as a flowchart in Figure 3.2

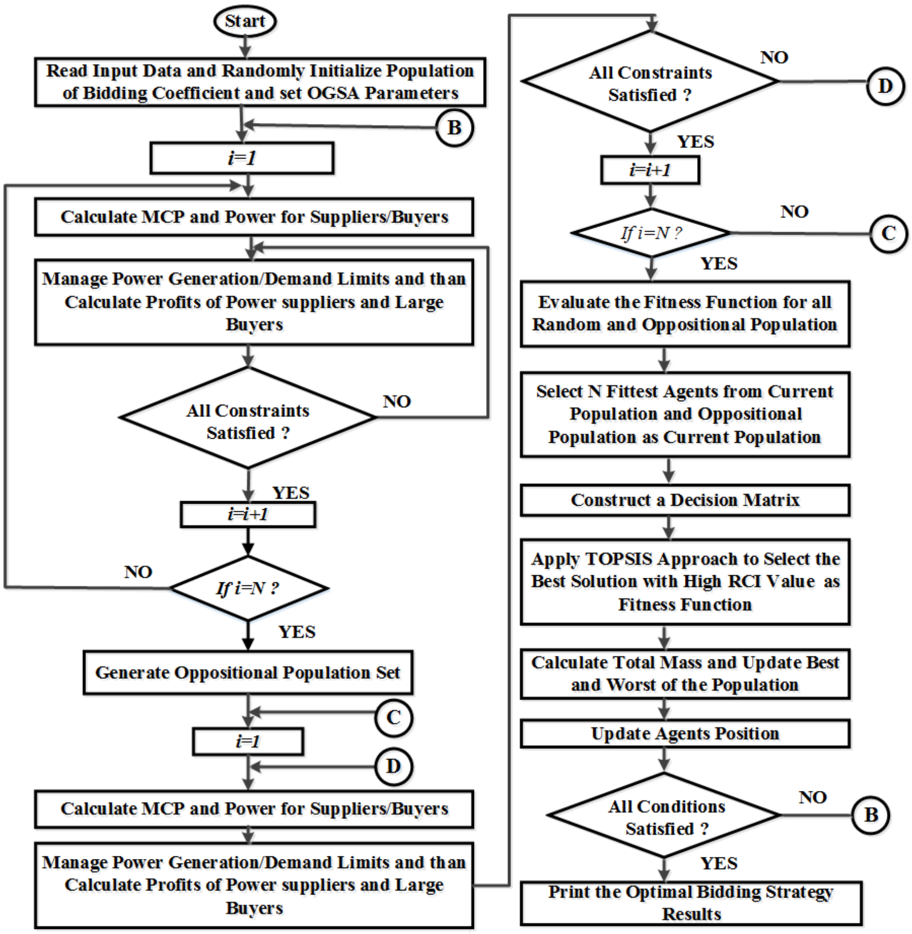


FIGURE 3.2: Solution approach as a flowchart using TOGSA

3.7 Result and Discussion

In this section, single sided and double sided bidding strategy have been evaluated to maximize profit of different market entities. For these strategies the modified heuristic techniques OGSA and TOGSA tested on different cases. Three cases have been considered as follows:

CASE I: Single side bidding strategy for profit maximization of power suppliers participating in single hour trading period using OGSA.

CASE II: Single side bidding strategy for profit maximization of power suppliers with ramp rate constraints participating in multi-hour trading period using OGSA.

CASE III: Double side bidding strategy for profit maximization of power suppliers and large buyers participating in single hour trading period using TOGSA.

3.7.1 CASE I

In this case, single side bidding strategy for profit maximization of power suppliers participating in single hour trading period is tested on IEEE 30-bus system with inelastic load demand 500 MW and solved by using OGSA. The generator data for IEEE 30-bus system is given in Table A.1 and taken from [11]. The results obtained using OGSA are compared to that of GSA , PSO [17] and binary coded GA method [22]. Also the results are compared with the Monte Carlo (MC) method [11]. The tuning parameters of proposed OGSA, GSA, PSO [17], and GA [22] methods are given in Table A.2. The simulation results are carried out in MATLAB 2012a on a 3.20 GHz, $i5$ processor, 4GB RAM PC. The considered value of coefficient $\alpha_{m,t}$ is kept fixed as $a_{m,t}$ and given in Table 3.1. The optimal values of bidding coefficients $\beta_{m,t}$ is searched from the interval between $[b_{m,t} \quad M \times b_{m,t}]$ and M is set to be 5. The optimum values of $\beta_{m,t}$ for different generators using proposed OGSA, GSA, PSO [17], GA [22] and MC [11] are given in Table 3.1.

TABLE 3.1: Optimal bidding coefficients of power suppliers

PSs	$\alpha_{m,t}$	$\beta_{m,t}$				
		MC [11]	GA [22]	PSO [17]	GSA	OGSA
1	2.00	0.158000	0.001045	0.001092	0.021004	0.026329
2	1.75	0.047450	0.048786	0.050953	0.090472	0.126153
3	1.00	0.130990	0.174234	0.181976	0.263500	0.352013
4	3.25	0.024580	0.023250	0.024283	0.054320	0.058808
5	3.00	0.056140	0.069694	0.072791	0.108594	0.157844
6	3.00	0.056140	0.069694	0.072791	0.108594	0.147336

Using the optimum bidding coefficients given in Table 3.1, the optimal bidding strategies like market clearing price (MCP), individual generator power and profits using proposed OGSA, GSA, PSO [17], GA [22] and MC [11] are shown in Table 3.2.

TABLE 3.2: Optimal bidding results for power suppliers

PSs	MC [11]		GA [22]		PSO [17]		GSA		OGSA	
	PG (MW)	Profit ($)	PG (MW)	Profit ($)	PG (MW)	Profit ($)	PG (MW)	Profit ($)	PG (MW)	Profit ($)
1	160	557	160	741.45	160	772.41	160	959.38	160	978.23
2	91.3	249	101.2	321.32	100.83	340.10	99.67	417.85	77.18	433.22
3	38.8	103	32.67	119.33	32.35	125.06	38.83	167.06	43.89	218.17
4	100	200	100	261.01	100	280.36	98.42	441.38	100	462.99
5	54.90	94	53	125.56	53.40	136.32	51.53	221.99	58.17	247.80
6	54.90	94	53	125.56	53.40	136.32	51.53	221.99	60.76	257.87
MCP ($/MW)	6.08		6.69		6.88		8.59		8.71	
TP ($)	1297		1694.23		1790.57		2429.65		2595.28	
TPG (MW)	499.99		499.99		499.99		499.99		500	

From Table 3.2, it is noted that the total profit (TP) obtained using OGSA is higher than that of GSA, PSO [17], GA [22] and MC [11] by \$165.63, \$804.71, \$901.05 and \$1298.28 respectively. Also, the profit is directly related to revenue and the revenue is calculated by using MCP. For the same amount of megawatt generation the MCP is changing therefore the profit indeed. Graphical representation of profit comparison with different methods are shown in Figure 3.3.

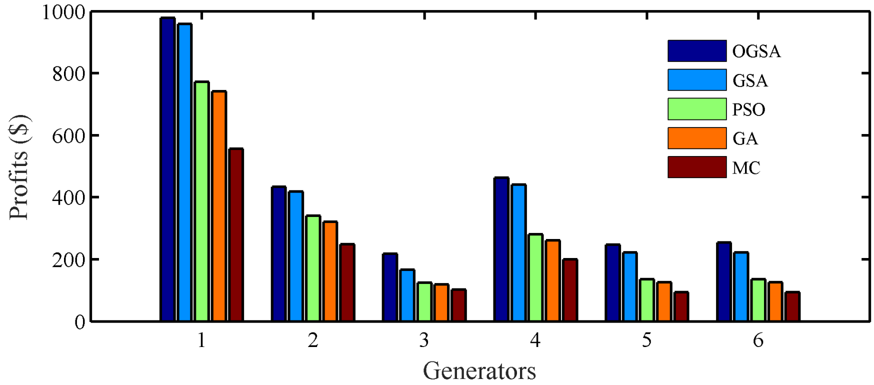


FIGURE 3.3: Comparative profit assessment of generators

This profit is further increased for higher system and for longer biding duration. It is also observed from Table 3.2 that the total power generation (TPG) obtained using OGSA method is exactly equals to the load demand. It shows that the error between the generation and load demand is zero for OGSA method.

3.7.2 CASE II

In this case, single side bidding strategy for profit maximization of power suppliers with ramp rate constraints participating in multi-hour trading period is tested on a example of six generators for 24 hours load profile and solved by using OGSA. Firstly, OGSA is tested on a system of six generators having load demand of 1033 MW for single hour trading period of power suppliers' profit maximization as a base study. Further, it is analyzed with other well known established methods such as GA, PSO and GSA using the statistical results. Then, a proposed bidding strategy for profit maximization of power supplier of six generators with the consideration of ramp rate for 24 hours trading period is being investigated using OGSA. The results are presented without and with ramp rates using OGSA. The generator data for six generators with ramp rates are given in Table A.3 and load data for 24-hours is given in Table A.4 The simulation are carried out using MATLAB R2014a on 3.20 GHz, $i5$ processor, 4GB RAM PC. The best tuned parameters for proposed OGSA, GSA, PSO and GA are given in Table A.2. Bidding coefficients of power suppliers are calculated similarly as explained in CASE I. Only the value of M is changed to 10 in this case. This assumption is kept unchanged for single and 24 hours. Here, the optimal bidding strategy for system of six generators with load demand of 1033 MW is investigated using proposed OGSA, standard GSA, PSO and GA in single hour trading period for power suppliers profit maximization. The MCP and net profits evaluated at corresponding optimal bidding coefficients as given in Table 3.3 obtained using GA, PSO, GSA and OGSA are 5.35 $/MW, 5.43 $/MW, 5.46 $/MW, 5.48 $/MW and $ 1265.21, $ 1328.61, $ 1362.6, $ 1394.67 respectively. The optimal coefficient values and net profit using proposed OGSA and other methods for comparison are presented in Table 3.3 and Table 3.4 respectively. It can be observed from the Table 3.4, that OGSA is getting higher MCP and highest profit amongst all the methods. This proves the effectiveness of OGSA in terms of results.

Table 3.3: Optimal bidding coefficients of power suppliers for single hour trading period

PSs	$\alpha_{m,t}$	$\beta_{m,t}$			
		GA	PSO	GSA	OGSA
1	4.10	0.003359	0.003409	0.003440	0.003539
2	4.50	0.034909	0.018594	0.021818	0.035696
3	4.10	0.005428	0.005616	0.005368	0.005467
4	3.74	0.028061	0.038421	0.038694	0.035635
5	3.82	0.005037	0.006140	0.006722	0.006149
6	3.78	0.035641	0.030983	0.032325	0.040405

Table 3.4: Optimal bidding results for single hour trading period

PSs	GA		PSO		GSA		OGSA	
	PG (MW)	Profit ($)	PG (MW)	Profit ($)	PG (MW)	Profit ($)	PG (MW)	Profit ($)
1	371.48	426.25	385.58	469.4	392.2	490.3	387.1	493.5
2	30	22.74	46.54	36.31	40.88	34.03	30	26.69
3	229.53	261.96	232.78	282.5	250.2	310.2	249.2	315.0
4	60	85.02	60	89.46	60	91.53	60	92.94
5	298.95	407.79	258.22	377.2	240.8	362.5	266.7	403.7
6	43.04	61.45	49.88	73.76	48.86	74.1	40	62.79
MCP	5.35		5.43		5.46		5.48	
TP	1265.21		1328.61		1362.6		1394.67	
TPG	1033		1033		1033		1033	

Further, to compare the algorithms robustness, the quality solutions of 100 trials for all considered algorithms are obtained and presented in Table 3.5. It can be observed from the Table 3.5 that proposed OGSA is getting better results in terms of mean and standard deviation showing OGSA strength.

TABLE 3.5: Performance comparison of considered algorithm for six supplier system

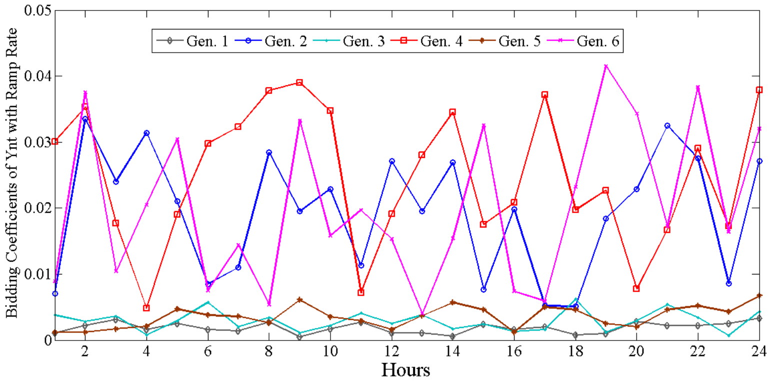
TP	GA	PSO	GSA	OGSA
Best	1265.21	1328.61	1362.60	1394.66
Worst	1117.81	1200.75	1268.19	1287.44
Mean	1166.54	1234.83	1297.44	1313.86
SD	31.85	29.60	28.15	24.40

On the basis of this, the proposed bidding strategy for profit maximization of power suppliers with and without ramp rate is evaluated using OGSA for trading period of 24 hours. The values of bidding coefficient $\alpha_{m,t}$ is kept constant for 24 hours and optimal values of bidding coefficient $\beta_{m,t}$ are obtained using OGSA. Finally, MCPs are calculated using the coefficients $\alpha_{m,t}$ and $\beta_{m,t}$ for every hour. These procedures are systematically estimated for both with and without ramp rates. The bidding coefficients for all six generators are plotted for both with and without ramp rates shown in Figure 3.4.

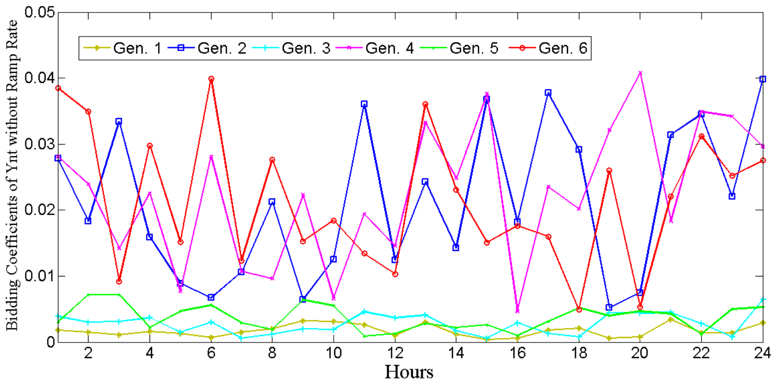
Similarly, MCPs with and without ramp rates are shown in Figure 3.5 for each hour. From Figure 3.5, it can be assessed that in case of ramp rates, MCPs value varies dynamically for each hour in contrast to without ramp rates which exhibit sudden variation while operating in same levels for many hours showing the inadequacy of method to apprehensive the realistic state of generators operation. Thus, ramp rate is essential to measure dynamics of generator operation which is here correlated with obtained MCPs.

Based on obtained bidding coefficients and MCPs values, generator dispatch and their corresponding profit is evaluated. The individual generator power dispatch and their profits are shown in Figure 3.6, Figure 3.7 and Table 3.6 respectively. Graphical representation of Table 3.6 is shown in Figure 3.8.

From Figure 3.5, it can be observed that the lesser values of the bidding coefficients are with ramp rates as compared to without ramp rates in the majority of hours contemplating the higher values of MCPs. Thus, results in increased profit of generators by \$ 1612 in comparison to without ramp rates. This is shown in Figure 3.9. This profit may be further increased for larger system with longer biding duration.



(a) Values of $\beta_{m,t}$ for different generators with ramp rates



(b) Values of $\beta_{m,t}$ for different generators without ramp rates

FIGURE 3.4: Values of $\beta_{m,t}$ for different generators with and without ramp rates

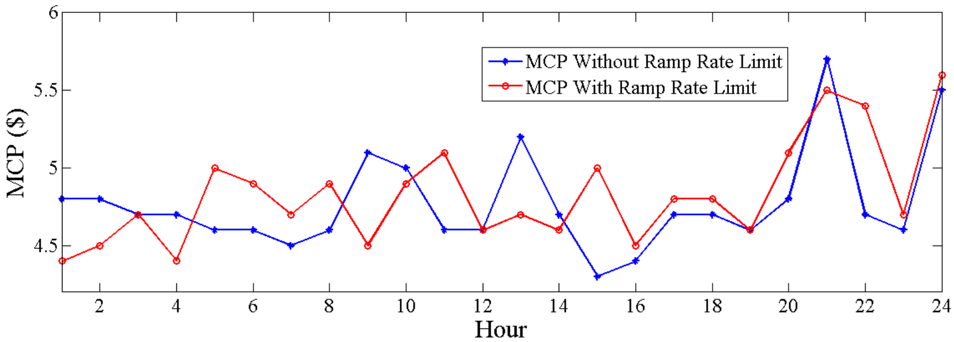


FIGURE 3.5: Market clearing price (MCP) with and without ramp rates

3.7.3 CASE III

In this case, double side bidding strategy for profit maximization of power suppliers and large buyers participating in single hour trading period is formulated as a multi-objective problem. Formulated problem is tested on a system having six power suppliers and two

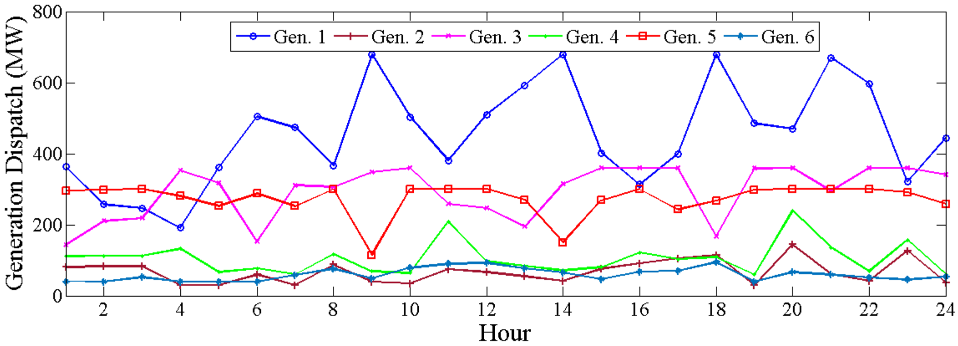


FIGURE 3.6: Generation dispatch with ramp rates

TABLE 3.6: Profit of individual generators with and without ramp rates

Hr	Profit of generators without ramp rates						Profit of generators with ramp rates					
	1	2	3	4	5	6	1	2	3	4	5	6
1	543.56	27.92	251.19	95.39	459.53	64.42	497.32	66.42	201.07	163.46	469.96	66.41
2	641.52	27.92	313.2	95.39	214.07	64.42	359.77	67.47	288.72	165.51	472.59	66.41
3	668.3	27.92	250.3	98.7	189.34	134.95	346.68	67.55	298.16	165.68	475.78	85.45
4	508.81	36.9	236.69	110.61	460.85	80.55	271.69	29.41	460.06	185.93	448.32	66.41
5	495.28	27.92	424.24	157.24	263.16	80.62	494.67	29.41	418.85	107.31	407.3	66.41
6	838.03	27.92	229.24	95.39	227.75	64.42	672.01	52.71	212.82	121.41	458.7	66.41
7	386.43	55.35	450.49	153.98	416.61	135.48	635.82	29.41	412.05	98.37	406.74	93.72
8	413.1	56.69	450.49	180.19	460.85	118.74	502.57	69.89	406.59	170.37	475.78	116.78
9	469.65	80.86	450.49	139.48	374.1	162.02	872.8	37.19	455	111.2	193.71	79.98
10	445.74	57.64	450.49	237.52	391.51	137.92	670.46	33.02	468.41	104.29	475.78	120.62
11	420.06	82.31	299.19	210.04	460.85	193.56	520.93	62.86	349.1	241.5	475.78	134.56
12	659.32	61.98	240.54	157.09	460.85	168.54	678.46	57.89	334.31	147.31	475.78	137.82
13	545.86	55.28	396.59	143.86	460.85	115.86	774.29	49.23	268.61	131.78	433.14	118.78
14	652.72	37.3	436.93	111.3	460.85	81.28	872.8	39	416.03	114.24	250.13	102.81
15	735.55	27.92	429.85	95.39	286.48	64.42	547.71	63.64	468.41	126.18	430.22	75.69
16	634.73	55.86	184.16	213.5	460.85	117.03	434.08	72.01	468.41	174.72	475.78	105.73
17	506	49.09	450.49	132.26	460.85	128.89	543.15	78.3	468.41	154.42	393.47	109.62
18	497.71	78.75	450.49	197.09	404.69	193.56	872.8	82.21	233.01	161.08	429.72	139.41
19	838.96	50.62	197.18	135.07	355.9	106.51	649.52	29.41	467.03	98.37	474.05	66.41
20	838.96	74.28	302.11	170.03	432.25	193.56	631.01	89.92	468.41	253.52	475.78	103.99
21	657.61	59.85	450.49	190.73	460.85	165.96	861.59	53.27	393.17	189.03	475.78	94.91
22	640.15	71.35	361.92	177.5	460.85	151.78	780.44	39.82	468.41	110.87	475.78	83.73
23	574.27	62.46	450.49	158.08	341.32	131.01	443.27	85.9	468.41	207.57	463.62	74.75
24	644.34	30.8	298.32	100.73	460.85	101.69	598.96	35.68	446.03	98.37	414.95	86.88

large consumers and solved by using TOGSA. System data is taken from [32] and given in Table A.5. In addition, considered value of constant load is 300 MW with load price elasticity (k=5) for aggregate demand at the time of bidding for considered system. The obtained results using TOGSA is compared with TGSA and MC [32] to prove the potential of TOGSA. The simulation results are carried out using MATLAB R2014a on 3.20 GHz, $i5$ processor, 4GB RAM PC.

The suppliers and large buyers fix the value of bidding coefficients $\alpha_{m,t}$ and $\phi_{n,t}$, and employs the TOGSA to determine the optimal values of bidding coefficients $\beta_{m,t}$ and $\varphi_{n,t}$ for developing its strategic bidding. The optimal values of bidding coefficients $\beta_{m,t}$ and $\varphi_{n,t}$

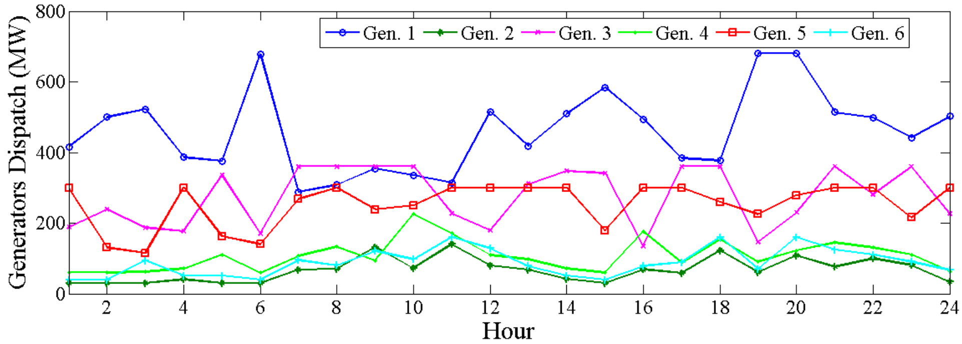
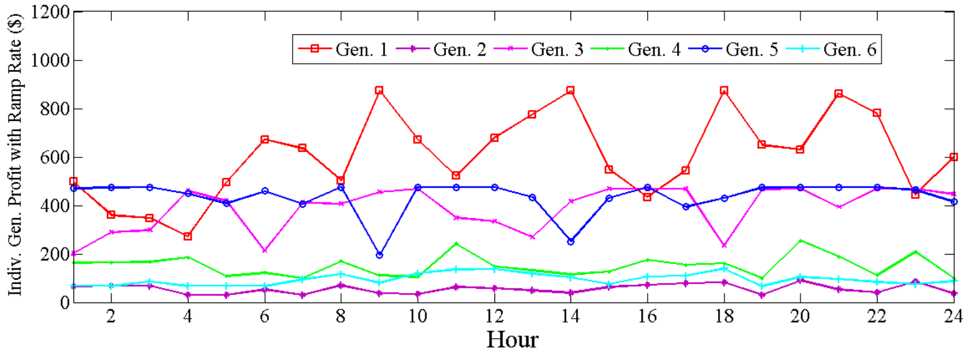
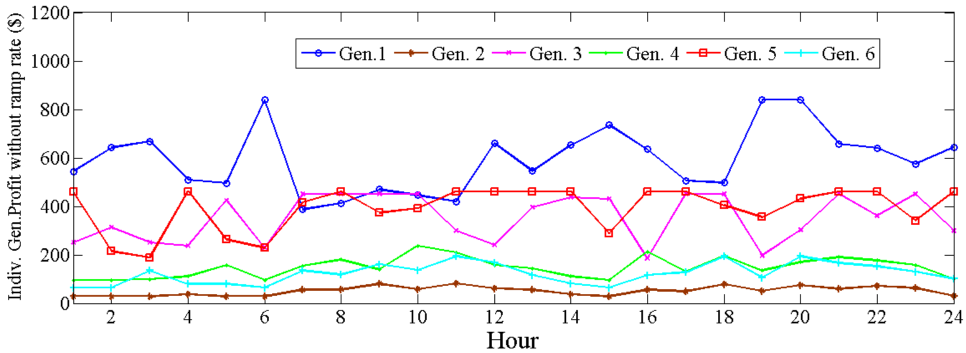


FIGURE 3.7: Generation dispatch without ramp rates



(a) Profit of individual generators for each hour with ramp rates



(b) Profit of individual generators for each hour without ramp rates

FIGURE 3.8: Profit of individual generators for each hour with and without ramp rates

is searched from the interval between $[b_{m,t} \quad M \times b_{m,t}]$ and $[f_{n,t} \quad M \times f_{n,t}]$ whereas M is set to be 10 [32].

Considered system has been already investigated in strategic bidding problem considering suppliers and buyers in [32]. Therefore, the proposed formulation has been firstly tested on considered system and solved by using weighted sum method along with OGSA (WOGSA). Figure 3.10 show that the weighted normalized solutions or Pareto-set for multi-objective

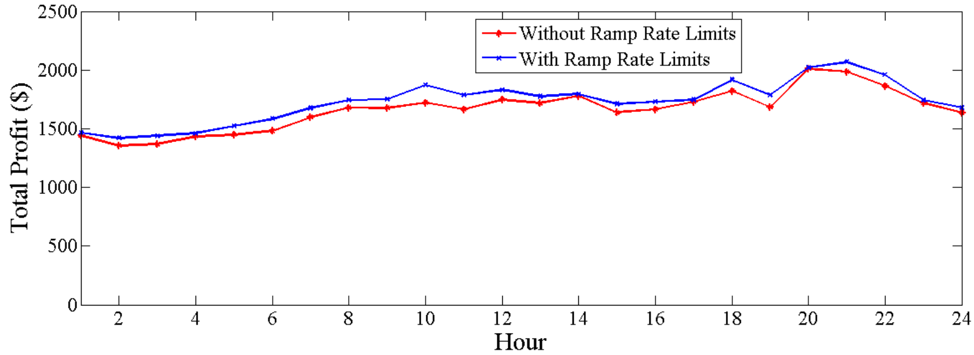


FIGURE 3.9: Comparative total profit assessment of generators with and without ramp rates

strategic bidding problem using WOGSA for considered system. Pareto-set results provid-

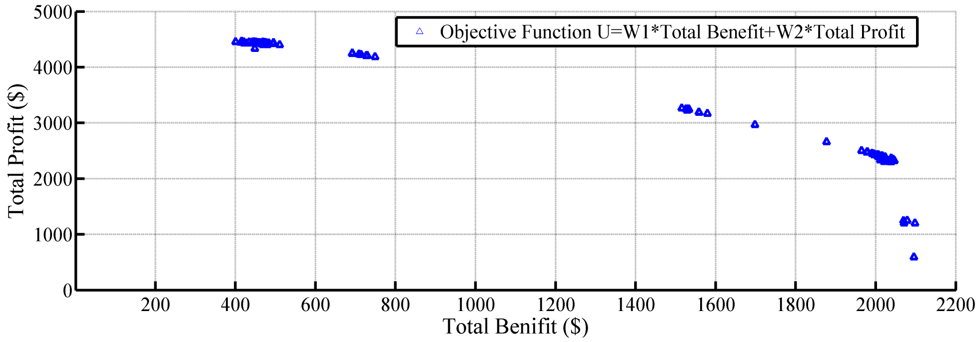


FIGURE 3.10: Pareto-set for considered system using OGSA along with weighted sum method

ed by the solution for each objective is different for different weights. But the difficulty is arising to find best results of individual objectives and best compromising results. Therefore, TOPSIS technique is applied to find best compromising result. The optimal bidding results of different suppliers/large buyers for considered system using WOGSA are presented in Table 3.7. Using the obtained optimal bidding coefficients $\alpha_{m,t}$, $\beta_{m,t}$, $\phi_{n,t}$ and $\varphi_{n,t}$ as in Table 3.7, market clearing prices (MCP) are evaluated. The evaluated MCP using WOGSA is higher than WGSA but lower than MC [32] approach. It is observed from Table 3.7 that the overall profit of suppliers is increased by $463.29 using WOGSA as compared to WGSA. On the other hand, overall profit can be further increased by $344.14 using MC [32] approach. However, the overall benefit of buyers using WOGSA and WGSA [25] is increased by $ 158.6 and $ 225.9 as compared to MC [32] approach. WGSA also seems more suitable for the buyers' benefit.

In the light of above discussion authors concluded that the considered objectives are contradictory in nature. The formulated problem cannot be handled as a true multi-objective

Table 3.7: Optimal bidding results for considered system using weighted sum method along with OGSA

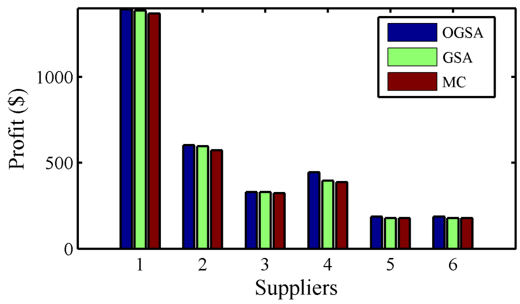
PSs	$\alpha_{m,t}$	MC [32]			WGSA			WOGSA		
		$\beta_{m,t}$	PG (MW)	Profit ($)	$\beta_{m,t}$	PG (MW)	Profit ($)	$\beta_{m,t}$	PG (MW)	Profit ($)
1	6.0	0.02927	160	1368	0.024071	160	1148.9	0.01905	160	1308.06
2	5.25	0.12420	89.4	572.7	0.485757	67.76	418.3	0.491757	77.6	516.14
3	3.0	0.29231	45.7	322.9	0.406048	67.27	183.74	1.144278	67.6	248.8
4	9.75	0.07433	88.8	386.4	0.124349	79.82	256.19	0.208625	77.44	330.24
5	9.0	0.17058	43.1	177.5	0.372618	57.76	95.22	0.50157	67.6	128.81
5	9.0	0.17058	43.1	177.5	0.620758	57.76	95.22	0.756491	67.6	128.81
Tot.			470.1	3005		490.37	2197.57		517.8	2660.86
LBs	$\phi_{n,t}$	$\varphi_{n,t}$	CD (MW)	Benefit ($)	$\varphi_{n,t}$	CD (MW)	Benefit ($)	$\varphi_{n,t}$	CD (MW)	Benefit ($)
1	30	0.09771	139.7	1126.3	0.075904	197.87	1405.78	0.094949	147.71	1198.8
2	25	0.07719	112.1	592.6	0.148658	67.4	539.02	0.037304	150	678.7
Tot.			251.8	1718.9		265.27	1944.8		297.71	1877.50
MCP			16.35			14.98			15.98	
FD			218.3			225.1			220.12	
TPT			470.1			490.37			517.8	
T(P+B)				4723.1			4142.37			4538.36

optimization problem using weighted sum method. This limits the search capability for the optimal solution. Thus, it becomes important for an algorithm to identify the overall optimal operating point considering both entities (Suppliers and Buyers) together. Therefore, TOPSIS technique is applied to find out the best compromising result. It is fundamentally an effective method for multi-objective problem that decreases the Euclidean distance of Pareto-set from best result of individual objects and provides best compromising solution.

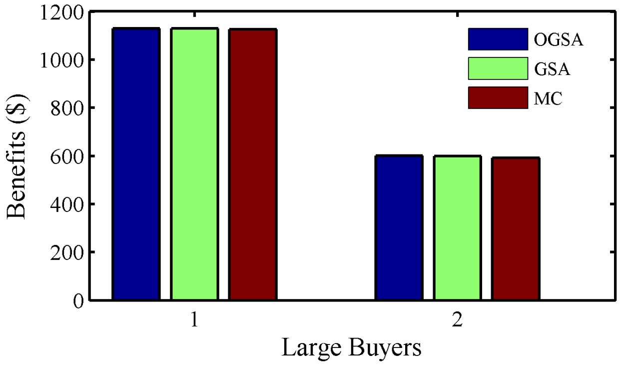
Table 3.8: Optimal bidding results for considered system using TOPSIS along with OGSA

PSs	$\alpha_{m,t}$	MC [32]			TGSA			TOGSA		
		$\beta_{m,t}$	PG (MW)	Profit ($)	$\beta_{m,t}$	PG (MW)	Profit ($)	$\beta_{m,t}$	PG (MW)	Profit ($)
1	6.0	0.02927	160	1368	0.037574	160	1386.6	0.053632	160	1391.8
2	5.25	0.12420	89.4	572.7	0.119268	114.2	596.2	0.143785	103.5	601.83
3	3.0	0.29231	45.7	322.9	0.449634	50.09	329.52	0.646152	46.15	330.11
4	9.75	0.07433	88.8	386.4	0.098465	88.35	395.73	0.030936	120	445.22
5	9.0	0.17058	43.1	177.5	0.673058	40.15	178.85	0.480586	45.26	185.75
6	9.0	0.17058	43.1	177.5	0.673058	40.15	178.85	0.480586	45.26	185.75
Tot.			470.1	3005		492.9	3065.7		520.2	3140.4
LBs	$\phi_{n,t}$	$\varphi_{n,t}$	CD (MW)	Benefit ($)	$\varphi_{n,t}$	CD (MW)	Benefit ($)	$\varphi_{n,t}$	CD (MW)	Benefit ($)
1	30	0.09771	139.7	1126.3	0.090492	149.6	1129.4	0.088446	152.7	1128.9
2	25	0.07719	112.1	592.6	0.067894	125.7	598.7	0.048842	150	600.2
Tot.			251.8	1718.9		275.3	1728.1		302.7	1729.1
MCP			16.35			16.47			16.50	
FD			218.3			217.6			217.5	
TPT			470.1			492.9			520.2	
T(P+B)				4723.1			4793.8			4869.5

The optimal values of bidding coefficients $\alpha_{m,t}$, $\beta_{m,t}$, $\phi_{n,t}$ and $\varphi_{n,t}$ of different suppliers and large buyers for considered system using TOPSIS along with OGSA (TOGSA) are presented in Table 3.8. The evaluated MCP using TOGSA is higher than TGSA and MC [32]. The MCP is proportionally related to profit through revenue. It is observed from Table 3.8 that the overall profit of suppliers is increased using TOGSA as compared to TGSA by \$74.7 and MC [32] by \$135.4. Also, the overall benefit of buyers using TOGSA is increased as compared to TGSA by \$1 and MC [32] by \$10.2. TOGSA provides an optimal MCP that maximizes the profit/benefit of suppliers/buyers. Thus, it further encourages both entities to increase the trade of power. It is also observed from the Table 3.8, that TOGSA results in 27.3 MW more power traded than TGSA and 50.1 MW as compared to MC [32]. The value of objective functions summation considering double sided bidding using TOGSA is increased as compared to TGSA by \$75.7 and MC [32] by \$145.5. Graphical representation of profit and benefit comparison of each power supplier/large buyer with TOGSA, TGSA and MC [32] methods for considered system is shown in Figure 3.11.



(a) Comparison of profit for individual power supplier



(b) Comparison of benefit for individual buyer

FIGURE 3.11: Profit and benefit comparison of each power supplier and large buyer for IEEE 30-bus system

3.8 Conclusions

In this chapter, two type of bidding strategy namely single and double side have been evaluated for profit maximization of different market entities. Firstly, single side bidding is tested in single and multi period with power balance and maximum/minimum generation constraints. The ramp rate constraints is being considered in later part. After that double side bidding strategy is investigated with same constraints as in former case.
Firstly, single side bidding strategy for profit maximization of power suppliers participating in single hour trading period is solved using OGSA. The experimental outcomes in this case shows that the proposed OGSA getting better results compared to other reported techniques in terms of result quality. Then, in multi hour trading period with and without ramp rate is solved using OGSA. The consideration of ramp rates provides practically feasible values of generation dispatch off each unit and the results obtained clearly indicate that the participation of generators in a day ahead electricity market bidding process without considering ramp rate limits will cause economic loss to the generators as this extra cost is beared by generators.
Secondly, double side bidding strategy for profit maximization of power suppliers and large buyers participating in single hour trading period is formulated as a multi-objective problem and solved by using TOGSA. In this problem, six power suppliers and two large buyers have been considered in a day-ahead electricity market. The proposed techniques are successful increasing the trading of power between suppliers and buyers and thus the value of MCP and objective functions has been improved compared to other reported techniques in terms of result quality. Moreover, the total power output of suppliers is exactly equal to addition of the buyer's demand and forecasted load demand.

The next Chapter exclusively has been devoted on bidding strategies with the inclusion of renewable energy sources. In addition, uncertainties and limitations associated with renewables have been modeled using an appropriate mathematical model for calculation of market clearing price (MCP). This proposed approach is investigated on both single and double side bidding mechanisms for a single hour trading period.

Chapter 4

Bidding Strategies for Electricity Market Participants with Amalgamation of Renewable Power

4.1 Introduction

During the recent years, renewable energy sources (RESs) production plays a vital role in moving towards a green economy. Due to this reason, RESs are under prime concern with the annihilation of fossil fuels along with carbon emissions, which further draw the interest of researchers [50]. As a part of the strategic bidding of conventional generators, the GENCOs having renewable generation also participate in the bidding process. Electrical power productions and percent of installed capacities of wind and solar power plants go higher and will turn into the significant power generators soon [49]. This has led to the new dimensions of exploration in optimal bidding strategy with amalgamation of wind and solar based power generation. The main disadvantage of wind and solar power production is its uncertainty and unpredictable nature of wind speed and solar irradiation which always results in deviation from the actual generation. In the deregulated environment, the uncertainty of wind and solar power has increased the problems manifold for the producers in devising an optimal bidding strategy with CPS. Therefore in this chapter, optimum bidding strategies such as single sided for power supplier and double sided for power suppliers and large buyer have been formulated with amalgamation of substantial wind and solar based power generation. Moreover, the wind and solar are used as probabilistic manner to model the uncertainty and their prediction error are considered in cost function using underestimation and overestimation.

4.2 Modeling of Renewable Power Sources

In this section, modeling of solar irradiation and wind speed is elaborated. Solar irradiation is modeled using Beta Probability Distribution Function (BPDF) and wind speed is modeled through Weibull Probability Distribution Function (WPDF). The power probability distributions obtained from respective models are used in further simulations.

4.2.1 Modeling of wind power

To build the optimal strategic bidding in the presence of wind power, handling of uncertainty associated with wind speed has required. Data for wind speed at the considered location of Barnstable city, MA, USA, follow a WPDF. The WPDF is given by [87, 88] as

$$W_{PDF} = \frac{k}{c}\left(\frac{v}{c}\right)^{(k-1)}\left(exp\left(-\frac{v}{c}\right)^{k}\right) \tag{4.1}$$

Wind speed characteristics depend on different factors such as, topography, geography etc. The reasonable frequency of wind speed in the target zone can be used for calculation [88]. There are different strategies accessible in the literature to assess Weibull parameters. The graphical technique for k and c estimation utilizing mean of historical wind speed (μ_{hws}) and standard deviation (σ_{std}) [89] as follows

$$k = \left(\frac{\sigma_{std}}{\mu_{hws}}\right)^{(-1.086)} \tag{4.2}$$

$$c = \left(\frac{\mu_{hws}}{\Gamma\left(1+\left(1/k\right)\right)}\right) \tag{4.3}$$

Historical information about the speed of the wind, as estimated by anemometers introduced at different heights in wind farms, is utilized in the generation of scenarios. Here, first, 1000 scenarios are generated randomly by using WPDF and these generated scenarios are changed over into power scenarios considering the hub heights. This procedure is fundamental because the hub heights of introduced turbines and anemometers' height are not the same in some situations [90]. This procedure has communicated as

$$v\left(h_{est}\right) = v\left(h_{rkh}\right)\left(\frac{h_g}{h_{kah}}\right)^{(\gamma)} \tag{4.4}$$

The generated scenarios for the preferred height of the hub are converting into power scenarios by utilizing the power curve for the measured model of wind turbine. The power calculation can be represented as

$$W_a\left(v\right) = \begin{cases} 0 & \mathrm{v} \leq \mathrm{v}_{in} \\ \frac{1}{2}\eta_p\left(v\right)\rho A_s v^3 & \mathrm{v}_{in} \leq v \leq v_r \\ W_r & \mathrm{v}_r \leq v \leq v_o \\ 0 & \mathrm{v} \geq \mathrm{v}_o \end{cases} \tag{4.5}$$

Equation (4.5) demonstrates the production of random and distinct wind power variables. Henceforth, it is essential to convert the distribution of available wind speed in terms of power to be utilized in the future. The probability of the linear part [88] in wind power output is defined as

$$f_w\left(\mathrm{v}_{in} \leq v \leq v_r\right) = \left(\frac{kzv_{in}}{cW_r}\right)\left[\frac{(1+zW_a/W_r)v_{in}}{c}\right] \times \left\{-\left[\frac{(1+zW_a/W_r)v_{in}}{c}\right]^k\right\} \tag{4.6}$$

Here, z is defined as $z = \frac{(v_r - v_{in})}{v_{in}}$

The probability of zero wind power output [88] is represented as

$$f_w\left[(\mathrm{v} \leq \mathrm{v}_{in}) \quad \text{and} \quad (\mathrm{v} \geq \mathrm{v}_o)\right] = 1 - \exp\left[-\left(\frac{v_{in}}{c}\right)^k\right] + \exp\left[-\left(\frac{v_o}{c}\right)^k\right] \tag{4.7}$$

The probability of maximum (rated) wind power output [88] is defined as

$$f_w(\mathrm{v}_r \leq v \leq v_o) = \exp\left[-\left(\frac{v_r}{c}\right)^k\right] + \exp\left[-\left(\frac{v_o}{c}\right)^k\right] \tag{4.8}$$

4.2.2 Modeling of Solar Power

It is necessary to handle the uncertainty associated with solar irradiation in order to deal with strategic bidding in the presence of solar power. Conversion of the solar irradiations is usually dependent upon the solar cell temperature, insolation of solar and technical properties of different PV modules. The output of solar power can be calculated by using solar irradiance and temperature [87], which can be expressed as

$$T_{cell,t} = T_a + S_{i,t}\left(\frac{T_{NO} - 20}{0.8}\right) \tag{4.9}$$

$$I_t = S_{i,t}\left[I_{sc} + I_{TK}\left(T_{cell,t} - 25\right)\right] \tag{4.10}$$

$$V_t = V_{oc} - V_{TK} \times T_{cell,t} \tag{4.11}$$

$$S_{PO,t}\left(S_{i,t}\right) = n \times I_t \times V_t \times FF \tag{4.12}$$

Here, FF is defined as $FF = \frac{I_{mpp} \times V_{mpp}}{I_{sc} \times V_{oc}}$
The irradiance of solar exhibit partial predictability because of sun orientation and restricted hours of accessibility. In this work, data for solar irradiation's are considered of Barnstable city, Massachusetts, USA. It is observed that this data follow a BPDF [91] which can be expressed as

$$B_{PDF}\left(S_{i,t}\right) = \left\{\frac{\Gamma\left(A_t + B_t\right)}{\Gamma\left(A_t\right)\Gamma\left(B_t\right)}\left(\frac{S_{i,t}}{S_{i\max,t}}\right)^{(A_t - 1)}\left(1 - \frac{S_{i,t}}{S_{i\max,t}}\right)^{(B_t - 1)}\right\}, \quad 0 \leq \left(\frac{S_{i,t}}{S_{i\max,t}}\right) \leq 1, \mathrm{A}_t > 0, \mathrm{B}_t > 0 \tag{4.13}$$

The value of BPDF parameters (A_t, B_t) are calculated by utilizing the mean (μ_{si}) and standard deviation (σ_{si}) of historical solar irradiation's data as follows

$$A_t = \mu_{si}^2\left(\frac{1 - \mu_{si}}{\sigma_{si}} - \frac{1}{\mu_{si}}\right) \tag{4.14}$$

$$B_t = A_t\left(\frac{1}{\mu_{si}} - 1\right) \tag{4.15}$$

Meanwhile, variables of BPDF lies in the interval range of (0, 1). Thus, a nominal value of solar irradiance is $\left(\frac{S_{i,t}}{S_{i\max,t}}\right)$ considered. Therefore, 1000 beta distributed scenarios are randomly generated, which are further converted into power scenarios corresponding to desirable Photo Voltaic module. The solar power pdf also follows BPDF as modeled [91]

$$B_{pdf}\left(S_{PV,t}\right) = \left\{\frac{1}{S_{PV}^{\max}} \times \frac{\Gamma\left(A_t + B_t\right)}{\Gamma\left(A_t\right)\Gamma\left(B_t\right)}\left(\frac{S_{PV,t}}{S_{PV,t}^{\max}}\right)^{(A_t - 1)}\left(1 - \frac{S_{PV,t}}{S_{PV,t}^{\max}}\right)^{(B_t - 1)}\right\}, 0 \leq \left(\frac{S_{PV,t}}{S_{PV,t}^{\max}}\right) \leq 1, \mathrm{A}_t > 0, \mathrm{B}_t > 0 \tag{4.16}$$

4.2.3 Wind and Solar Power Scenarios Reduction

After 1000 generated wind and solar power scenarios, it is conceivable that the probability of a few scenarios might be little or even some of the scenarios are the equivalent. It is important to overlook the invaluable scenarios (lower probability scenarios) and comparable scenarios. Subsequently, it is critical to decrease the arrangement of a unique scenario such that the reduced arrangements have fewer scenarios while the stochastic properties are not changed importantly. The quantity of diminished scenarios relies on the sort and nature of the issue to be optimized, and it must be short of what one-fourth of generated scenarios [90].

The primary objective of scenario reduction techniques is to eliminate the scenarios with low and same probabilities. In this manner, a subset of scenarios of their new probabilities are evaluated such that probability measure of reduced scenarios should remain close to the main probability measure in terms of probability distance between two probabilities. The scenario decrease technique minimizes and packages the scenarios, utilizing the Kantorovich Distance Matrix (KDM) [90], [92]. KD is the distance of probabilities between two different scenario arrangements that express a similar stochastic process. It is used to consider the closeness of various scenario arrangements for most part. KD guarantees that most extreme conceivable scenarios are decreasing without damaging a given resilience rule. The probability of all decreased scenarios are supposed to be zero. The new probability of ensured scenario is equivalent to the total of its previous probability and the probability of removed scenarios that are nearest to it. In KD technique, the following steps are used to scenarios reduction.

1. The KD is calculated for every combination of scenarios and create the KDM containing entire scenarios and relative distance to one another. The estimation of the distance between two scenarios υ^i and υ^j are given by

$$KD\left(\upsilon^i, \upsilon^j\right) = \left(\sum_{l=0}^{\eta_l} \left(\upsilon_l^i - \upsilon_l^j\right)^2\right)^{\frac{1}{2}} \tag{4.17}$$

2. Find a different closest scenario for every scenario υ^i, namely the scenario υ^j, j $\neq$ i of the minimum KD to asses scenario $\min\left\{KD\left(\upsilon^i, \upsilon^j\right)\right\}$. The recognized scenario can be effortlessly set apart in the KDM.

3. Corresponding to each combination of scenarios obtained in Step 2, calculate

$$\min\left\{KD\left(\upsilon^i, \upsilon^j\right)\right\} \times P\left[\upsilon^i\right] \tag{4.18}$$

   Next, the qualities for entire scenario sets are analyzed in KDM and the least important sets are identified. From two individuals of this set, the scenario which will be removed first is selected depending on the following conditions:

   (a) Comparative nearness to different scenarios too.

   (b) Low probability of occurrence.

4. Remove one scenario and construct new KDM. Subsequently, the probability of removed scenario is added to the probability of the scenario which is nearest to it.
5. Repeat Steps 2–4 to remove one scenario in every iteration until the stopping criterion reached.

Redistribution rule states that the modified probability of saved scenario is equivalent to the summation of all the prior probability and probabilities of removed scenarios which are nearest to the saved scenario when compared to concerning KD. Completely removed scenarios are assumed to have zero probability. Anyone of the following can be stopping criterion for the algorithm:

1. A pre-determined KD has met; this implies that all outstanding scenarios are isolated from one another by a required particular distance.
2. The preferred quantity of the final remaining scenarios has met. For instance, we wish to have ten representative scenarios toward the finish of emphasis from the underlying 1000 conceivable scenarios.

4.2.4 Estimation of Schedule Wind and Solar Power Amount for Bidding

The scheduled wind (W_g) and solar (S_g) power is obtained using KDM and the appropriate probabilities are calculated as follows

$$S_g = \sum_{i=1}^{v_i} S_{ai} \times \text{prob}_i \tag{4.19}$$

$$W_g = \sum_{i=1}^{v_i} W_{ai} \times \text{prob}_i \tag{4.20}$$

4.2.5 Wind and Solar Power Cost Evaluation

The scheduled wind and solar power at the time of delivery may not be equal to the generated wind and solar power output due to the stochastic nature of wind speed and solar irradiation respectively. Therefore, wind and solar generator can either be retained by the third party or in alternatively the market operator can maintain it. In the first instance, the third party agrees to offer a specific sum of power bound by the day-ahead agreement. However, if required power has not supplied, penalty cost is to be incurred by the third

party. In this work, later case has considered, in which the wind and solar generators are claimed by the market operator, and in this way, there will be no cost incurred in terms of penalty.
However, when there is an overestimation of wind power, either power is purchased from exchange sources, or load shedding is carried out to keep the power balance, then the same amount is reflected in terms of penalty addressing both economic and reliability concerns. Also, in case of wind and solar power underestimation, wind and solar generators need to decrease the produced power along these lines which results in wastage of available power limit and adverse impact on the environmental conditions [87]. Therefore, both these circumstances are contrary (one leans toward more reliance on wind and solar generators for power needs though alternate empowers the utilization of something beyond solid conventional generators) and also detrimental from the perspective of economy, environment, and reliability of operation. The condition of mismatch can be incorporated as imbalance term in cost function when wind and solar generation are owned by the system operator. This imbalance cost of wind and solar measures the difference in forecasted and actual power, which is summation of underestimation and overestimation cost. It can be expressed as

$$IMC(Wg_n) = O_c(w_g) + U_c(w_g) \tag{4.21}$$

$$IMC(Sg_n) = O_c(S_g) + U_c(S_g) \tag{4.22}$$

Here, it should be noted that condition of overestimation of wind power is more harmful as compared to underestimation of wind power. The evaluation of overestimation and underestimation cost of available wind and solar power are as follows:

4.2.5.1 Estimation of Overestimation Cost for Available Wind and Solar Power

The deficit in power is a decisive factor in evaluating the cost of overestimation of solar and wind power. The probability of this shortage incidence for a specified amount of scheduled solar and wind power is formulated as

$$O_c(w_g) = K_o \times \int_0^{W_g} (W_g - W_a) \times f_{W_a}(W_a) \times dW_a \tag{4.23}$$

$$O_c(S_g) = K_o \times \int_0^{S_g} (S_g - S_a) \times f_{S_a}(S_a) \times dS_a \tag{4.24}$$

4.2.5.2 Estimation of Underestimation Cost for Available Wind and Solar Power

The cost of underestimation depends on measure of actual solar and wind generation which is in surplus and the probability of occurrence of excess power. Therefore it does not indicate true cost rather it represents penalty term for wastage of available resources

$$U_c(w_g) = K_u \times \int_{W_g}^{W_{\max}} (W_a - W_g) \times f_{W_a}(W_a) \times dW_a \tag{4.25}$$

$$U_c(S_g) = K_u \times \int_{S_g}^{S_{\max}} (S_a - S_g) \times f_{S_a}(S_a) \times dS_a \tag{4.26}$$

4.3 Market Clearing Mechanism with Amalgamation of Renewable Power Suppliers in a POOL Based Energy Market

The functioning and formation of energy markets without considering wind and solar power suppliers were discussed in chapter 3. The MCP, in the competitive energy market, with and without renewable power, is different and can be considered in two ways. They will be permitted to bid on the market in option one and take the MCP plus some premium. In addition, the penalty for output variability must not be charged to renewable generators like other despatchable generators are charged for the same. There is a high risk of being dispatched on this condition. Because of the government's green energy commitments, this option is not appropriate. Also, the renewable generators are not competitive without government subsidies and the government would like to eliminate subsidies in the future. Another more attractive option is that renewable generator outputs can be brought into the system whenever and wherever they are available [50]. The MCP is to be determined in this condition to take care of both the renewable generation output and the renewable power variability. Since renewable power depends on renewable availability, the forecasting error is high, thus minimizing its impact on market price and system operation. The efficiency of the market can be improved with a proper pricing mechanism.

When the renewable power suppliers are incorporated in the single sided and double sided POOL based energy market, the power balance constraints and MCP are modified. The rest equations and procedure will remain same as described in chapter 3. The modified power balance constraints, MCP and objective functions are represented as

1. Power balance constraints

   (a) Single Side

$$\sum_{m=1,t=1}^{CPS,T} PG_{m,t} + \sum_{x=1,t=1}^{RPS,T} RG_{x,t} = D\left(R_{s,t}\right) \tag{4.27}$$

   (b) Double Side

$$\sum_{m=1,t=1}^{CPS,T} PG_{m,t} + \sum_{x=1,t=1}^{RPS,T} RG_{x,t} = D\left(R_{d,t}\right) + \sum_{n=1,t=1}^{LB,T} CD_{n,t} \tag{4.28}$$

2. MCPs

   (a) Single Side

$$R_{s,t} = \frac{D_{c,t} - \sum_{x=1,t=1}^{RPS,T} RG_{x,t} + \sum_{m=1,t=1}^{CPS,T} \frac{\alpha_{m,t}}{\beta_{m,t}}}{K + \sum_{m=1,t=1}^{CPS,T} \frac{1}{\beta_{m,t}}} \tag{4.29}$$

   (b) Double Side

$$R_{d,t} = \frac{D_{c,t} - \sum_{x=1,t=1}^{RPS,T} RG_{x,t} + \sum_{m=1,t=1}^{CPS,T} \frac{\alpha_{m,t}}{\beta_{m,t}} + \sum_{n=1,t=1}^{LB,T} \frac{\phi_{m,t}}{\varphi_{m,t}}}{K + \sum_{m=1,t=1}^{CPS,T} \frac{1}{\beta_{m,t}} + \sum_{n=1,t=1}^{LB,T} \frac{1}{\varphi_{n,t}}} \tag{4.30}$$

4.4 Problem Formulation in Single Side POOL Based Energy Market with Amalgamation of Renewable Power

With amalgamation of renewable power, the objective function for profit maximization of market participants in single side POOL based energy market is modified as
Maximize

$$F_S(\alpha_{m,t}, \beta_{m,t}) = R_{s,t} \times PG_{m,t} + R_{s,t} \times RG_{x,t} - PCS_{m,t}(PGS_{m,t}) - IMC_{x,t}(RG_{x,t}) \tag{4.31}$$

Subject to: Power balance constraints as given in equation (4.27), power inequality constraints as given in equation (3.4) and renewable power constraints as given in equations (4.21) and (4.22).

4.5 Problem Formulation in Double Side POOL Based Energy Market with Amalgamation of Renewable Power

With amalgamation of renewable power, the objective function for profit maximization of market participants in double side POOL based energy market is modified as
Maximizes

$$F_D(\alpha_{m,t}, \beta_{m,t}) = R_{d,t} \times PGD_{m,t} + R_{d,t} \times RG_{x,t} - PCD_{m,t}(PGD_{m,t}) - IMC_{x,t}(RG_{x,t}) \tag{4.32}$$

$$F_D(\phi_{n,t}, \varphi_{n,t}) = PCD_{n,t}(CD_{n,t}) - R_{d,t} \times CD_{n,t} \tag{4.33}$$

Subject to: Power balance constraints as given in equation (4.28), power and demand inequality constraints as given in equations (3.12) and (3.13), and renewable power constraints as given in equations (4.21) and (4.22).
The bid data of the rivals and their corresponding joint normal PDFs are estimated same as described in chapter 3. The proposed OGSA and TOGSA are respectively applied to solve the above stochastic single and double side optimization problem with amalgamation of renewable power.

4.6 Solution Methodology

4.6.1 Solution Procedure of OGSA Applied to Single Side Optimal Bidding Strategy problem with Amalgamation of Renewable Power

1. Set input data of considered test system, Wind and solar data as discussed in modeling of renewable power sources for single side bidding strategy and parameters of the proposed OGSA.

2. Set population size (N) and randomly generate initial population λ for bidding coefficient $\beta_{m,t}$ of power suppliers in the decided search space of the problem.

3. Determine the market clearing price as (4.29) and dispatch of each generator as (3.7).

4. Set power generation limits as (3.4) and system load balance as (4.27) then calculate profit of each power supplier as (4.31).

5. Generate opposite population ($O\lambda$) to the initial generated population (λ) in search space. Then determine the market clearing price as (4.29) and dispatch of each generator as (3.7).

6. Set power generation limits as (3.4) and system load balance as (4.27) then calculate profit of each power supplier as (4.31).

7. Evaluate the fitness function for all random (λ) and opposite ($O\lambda$) population.

8. Select N fittest agents from current (λ) and opposite population ($O\lambda$) as current population (λ).

9. Determine the mass of every agent as (2.4) and gravitational constant as (2.6) respectively.

10. Calculate all agents' acceleration as (2.5).

11. Update the respective velocity and position of the agent as (2.7).

12. If the maximum number of iterations are not exceeded go to Step 3, otherwise the procedure will be stopped and the optimum single side bidding strategy with amalgamation of wind power printed.

4.6.2 Solution Procedure of TOGSA Applied to Double Side Optimal Bidding Strategy Problem with Amalgamation of Renewable Power

1. Set input data of considered test system for double side bidding strategy and parameters of the proposed TOGSA.

2. Set population size (N) and randomly generate initial population λ for bidding coefficient $\beta_{m,t}$ of power suppliers in the decided search space of the problem.

3. Determine the market clearing price as (4.30), dispatch of each generator as (3.15) and demand of each large buyer as (3.16).

4. Set power generation limits as (3.12), demand limits as (3.13) and system load balance as (4.28) then calculate profit of each power supplier as (4.31) and benefit of each buyer as (4.32).

5. Generate opposite population ($O\lambda$) to the initial generated population (λ) in search space. Then determine the market clearing price as (4.30), dispatch of each generator as (3.15) and demand of each large buyer as (3.16).

6. Set power generation limits as (3.12), demand limits as (3.13) and system load balance as (4.28) then calculate profit of each power supplier as (4.31) and benefit of each buyer as (4.32).

7. Add the solution of (4.31) and (4.32) for all random (λ) and opposite ($O\lambda$) population respectively as $0.5 * [(3.21) + (3.25)]$.

8. Evaluate the solution of (4.31) and (4.32) for all random (λ) and opposite ($O\lambda$) population.

9. Select N fittest agents from current (λ) and opposite population ($O\lambda$) as current population (λ).

10. Construct a decision matrix as (2.9).

11. Apply TOPSIS approach to select the best solution of (4.31) and (4.32) with high RCI value according to (2.14) as fitness function and corresponding fittest agents.

12. Determine the mass of every agent as (2.4) and gravitational constant as (2.6) respectively.

13. Calculate all agents' acceleration as (2.5).

14. Update the respective velocity and position of the agent as (2.7).

15. If the maximum number of iterations are not exceeded go to Step 3, otherwise the procedure will be stopped and the optimum double side bidding strategy with amalgamation of renewable power printed.

4.7 Result and Discussion

In this section, single sided and double sided bidding strategy with inclusion of renewable energy sources have been evaluated to maximize profit of different market entities. A modified heuristic technique, OGSA is used to solve single sided bidding strategy and TOGSA is used to solve double sided bidding strategy. Three cases are considered as follows

1. CASE I: Single sided bidding strategy with inclusion of only wind power using OGSA in a single hour trading period.

2. Case II: Single sided bidding strategy with and without inclusion of only with wind, only with solar and combination of both wind and solar power using OGSA in a single hour trading period.

3. Case III: Double sided bidding strategy with inclusion of only wind power, only solar power and combination of both wind and solar power using TOGSA in a single hour trading period.

4.7.1 CASE I

In this case, modified test systems such as IEEE standard 30-bus and 57-bus are considered with the inclusion of wind power source to investigate the impact of wind source on the bidding strategy and data for both systems are given in Table A.1 and Table A.6 respectively. The considered forecasted load demands of both systems are 500 and 1500 MW, respectively. The historical single hour (12:00–13:00) average wind speed data of August 2005 at 39 m anemometer height is used for calculation of wind power and obtained from Barnstable city, MA, USA [93]. At the time of data recording of selected site, air density of the site and shear coefficients values are also recorded which are 1.242 kg/m^3 and 0.35, respectively. VENSYS-100 turbine model with 100 m hub height and 2.5 MW of capacity [94] is used to transform wind speed data into wind power production. In this work, the total of 80 wind turbines each of 2.5 MW with the full capacity of 200 MW is considered. The proposed bidding model is solved by proposed OGSA, GSA, PSO and GA in MATLAB R2014a on a 3.20 GHz, $i5$ processor, 4 GB random access memory personal computer. The parameters used for different techniques such as OGSA, GSA, PSO, and GA for both systems are given in Table A.2.

Curve fitting of the actual historical wind speed data for different distributions such as normal, Rayleigh, and Weibull distribution is shown in Figure 4.1. The values of log likelihood, mean, and variance for different distributions are summarized in Table 4.1. It can be observed from Table 4.1 that log likelihood in Weibull distribution is better as compared with other distributions. A higher value of log likelihood for Weibull distribution shows that data fits in the best way in this distribution.

By using the values of shape parameter and scale parameter given in Table 4.2, 1000

Table 4.1: Value of log likelihood, mean, and variance for the different distributions

	Normal Fit	Rayleigh Fit	Weibull Fit
Log Likelihood Value	-59.2052	-65.3438	-59.1945
Mean	5.25484	4.87676	5.25439
Variance	2.7568	6.4984	2.84011

scenarios for wind speed are generated. These generated scenarios are changed into power

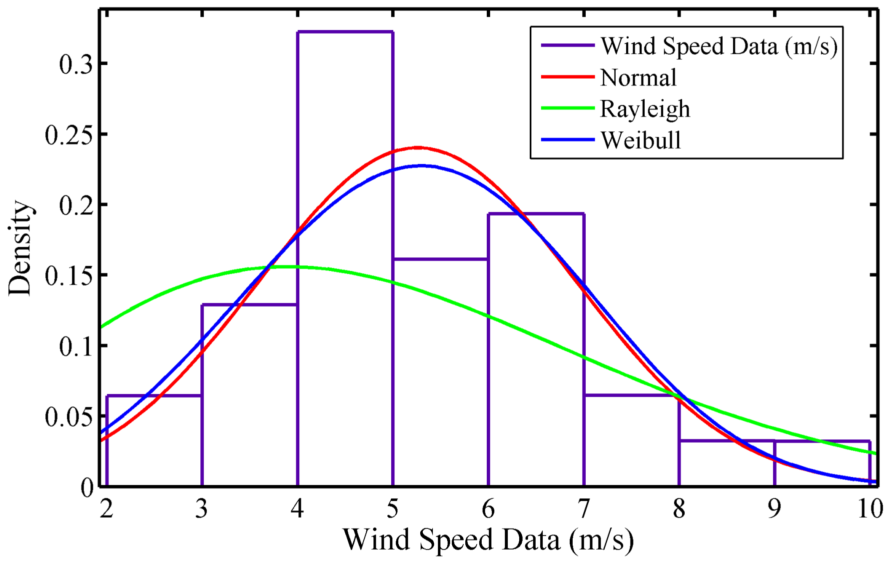


FIGURE 4.1: Curve fitting of the historical single hour (1200-1300 hrs) wind speed data of Barnstable city, MA, USA for different distributions

scenarios considering the desirable hub heights. After that probability of generated power scenarios is assigned by using Weibull distribution, then the probabilities associated with generated power scenarios is normalized such that their summation is equal to unity. Weibull and normalize Weibull probabilities density for generated power scenarios are shown in Figure 4.2.

A KDM method [90], [92] is used to reduce the scenarios for accurate modeling of wind

TABLE 4.2: Value of the shape parameter and the scale parameter of wind speed

Hub Height	Shape Parameter	Scale Parameter (m/s)
39 meter	3.49	5.84
100 meter	3.49	8.13

power uncertainty. This is performed as a large number of scenarios become quite cumbersome to model the uncertainty. Here, ten reduced scenarios are produced from 1000 generated scenarios. On the basis of these reduced scenarios, in the considered hour, wind power is scheduled. The final KDM with wind power outputs and their probabilities for reduced ten numbers of scenarios are given in Table 4.3. On the basis on wind power outputs and their probabilities, probable assessment of wind power is calculated for that hour. Probable value of wind power is 51.95 MW, considered as schedule wind power for that hour. The summation of reduced scenarios probabilities is always equal to unity.

After that, the strategic bidding model with and without wind power is solved by using

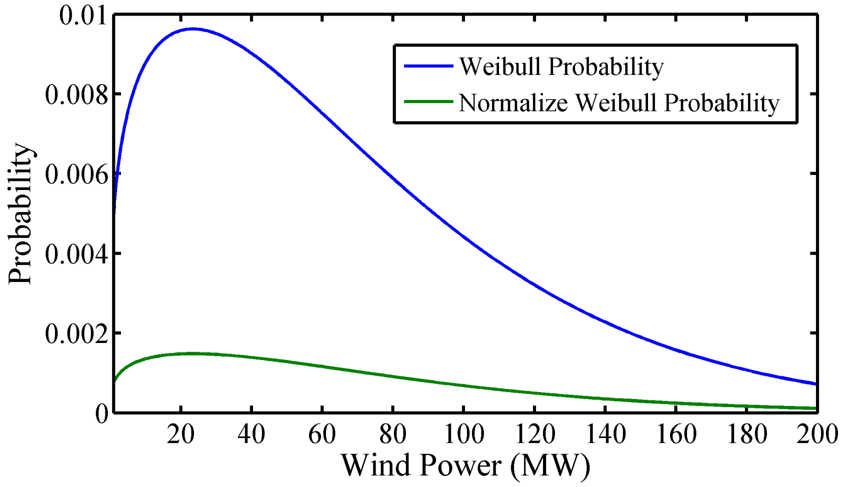


FIGURE 4.2: Weibull and normalize Weibull probability densities for generated power scenarios of single hour (1200-1300 hrs) wind speed data of Barnstable city, MA, USA

TABLE 4.3: Final KDM with wind power outputs and their probabilities for reduced ten numbers of scenarios

Index	1	2	3	4	5	6	7	8	9	10	W_a (MW)	Probability	Min (KD)
1	0	18.09	44.3	70.87	92.94	111.1	126.1	145.3	167.7	180.7	10.56	0.142	18.09
2	18.09	0	26.22	52.78	74.85	93.04	108	127.2	149.6	162.6	28.65	0.283	18.09
3	44.3	26.22	0	26.57	48.63	66.83	81.82	101	123.4	136.4	54.86	0.325	26.22
4	70.87	52.78	26.57	0	22.07	40.26	55.25	74.4	96.83	109.8	81.43	0.144	22.07
5	92.94	74.85	48.63	22.07	0	18.19	33.19	52.33	74.76	87.76	103.5	0.049	18.19
6	111.1	93.04	66.83	40.26	18.19	0	14.99	34.14	56.57	69.56	121.7	0.029	14.99
7	126.1	108	81.82	55.25	33.19	14.99	0	19.15	41.58	54.57	136.7	0.013	14.99
8	145.3	127.2	101	74.4	52.33	34.14	19.15	0	22.43	35.42	155.8	0.01	19.15
9	167.7	149.6	123.4	96.83	74.76	56.57	41.58	22.43	0	12.99	178.3	0.002	12.99
10	180.7	162.6	136.4	109.8	87.76	69.56	54.57	35.42	12.99	0	191.2	0.002	12.99

proposed OGSA, GSA, PSO, and GA for both systems. In the process of strategic bidding, the coefficients of bidding are not considered individually for maximization of profit for conventional generators. Owing to the inter-dependency of bidding coefficients, the values of one bidding coefficient considered as known values then values of other bidding coefficient are determined by using an optimization method [11]. Therefore, in this work, values of bidding coefficient $\alpha_{m,t}$ is fixed and employ the proposed OGSA, GSA, GA, and PSO to determine the optimum values of bidding coefficient $\beta_{m,t}$ from the search space between $[b_{m,t} \quad M \times b_{m,t}]$, M is set to be 10. The values of joint normal distribution parameters for the suppliers are obtained from [11].

First, the optimum values of bidding coefficients for IEEE standard 30-bus are obtained using proposed OGSA, GSA, PSO, and GA and given in Table 4.4. The optimal bidding strategy to clear the MCP for the IEEE standard 30-bus system is calculated after determining the optimal bidding coefficients using proposed OGSA, GSA, PSO, and GA. The

MCP and net profits evaluated at corresponding optimal bidding coefficients obtained using GA, PSO, GSA, and proposed OGSA are 12.55 $/MW, 12.89 $/MW, 13.9458 $/MW, 14.15 $/MW and $4490.02, $4672.93, $5212.6, $5317.72 respectively. From Table 4.4, it can be observed that among all the algorithms, OGSA is getting highest MCP and net profit. It can be shown that the OGSA is outperforming over both algorithms.

Similarly, for IEEE standard 57-bus system results are obtained and given in Table 4.5.

Table 4.4: Optimum bidding results for IEEE standard 30-bus

PSs	$\alpha_{m,t}$	GA $\beta_{m,t}$	GA PG (MW)	GA Profit ($)	PSO $\beta_{m,t}$	PSO PG (MW)	PSO Profit ($)	GSA $\beta_{m,t}$	GSA PG (MW)	GSA Profit ($)	OGSA $\beta_{m,t}$	OGSA PG (MW)	OGSA Profit ($)
1	2.0	0.044090	160	1592.4	0.042666	160	1645.73	0.049231	160	1815.32	0.049984	160	1848.47
2	1.75	0.19429	75.05	712.19	0.211031	74.81	735.14	0.224134	77.45	839.65	0.223528	78.68	867.49
3	1.0	0.300167	57.94	459.54	0.436374	49.28	433.95	0.722945	40.95	425.33	0.680919	42.5	446.15
4	3.25	0.094465	100	846.85	0.103585	100	880.18	0.097653	100	986.18	0.099466	100	1006.9
5	3.0	0.280553	53.50	439.52	0.275273	57.95	488.96	0.289934	60.80	573.06	0.307913	59.41	574.36
6	3.0	0.280553	53.50	439.52	0.275273	57.95	488.96	0.289934	60.80	573.06	0.307913	59.41	574.36
MCP			12.55			12.89			13.9458			14.15	
TP			4490.02			4672.93			5212.6			5317.72	
TPG			500			500			500			500	

From Table 4.5, it can be seen that obtained MCP and corresponding calculated net profit at optimality using GA, PSO, GSA and proposed GSA are 12.19 $/MW, 12.35 $/MW, 12.87 $/MW, 12.97 $/MW and $13,244.65, $13,457.81, $14,065.79, $14077.77, respectively.

Now, to measure the effect of wind source is considered in the both IEEE standard 30-bus

Table 4.5: Optimum bidding results for IEEE standard 57-bus

PSs	$\alpha_{m,t}$	GA $\beta_{m,t}$	GA PG (MW)	GA Profit ($)	PSO $\beta_{m,t}$	PSO PG (MW)	PSO Profit ($)	GSA $\beta_{m,t}$	GSA PG (MW)	GSA Profit ($)	OGSA $\beta_{m,t}$	OGSA PG (MW)	OGSA Profit ($)
1	1.7365	0.019718	530.23	5065.65	0.020393	520.21	5058.66	0.021819	510.26	5238.34	0.022239	505.16	5241.2
2	10	0.095015	23.07	45.23	0.098836	23.73	50.02	0.092598	30.99	79.34	0.076760	38.7	99.99
3	7.1429	0.078495	64.32	295.35	0.082602	62.98	299.48	0.081198	70.53	368.62	0.088860	65.58	351.7
4	10	0.095015	23.07	45.23	0.098836	23.73	50.02	0.092598	30.99	79.34	0.076760	38.7	99.99
5	1.81	0.020843	498.08	4724.32	0.021487	490.31	4732.82	0.02278	485.52	4945.47	0.023240	480.23	4944.7
6	10	0.095015	23.07	45.23	0.098836	23.73	50.02	0.092598	30.99	79.34	0.076760	38.7	99.99
7	2.4390	0.028839	338.18	3023.63	0.02788	355.31	3216.81	0.030615	340.71	3275.32	0.031635	332.92	3240.2
MCP			12.19			12.35			12.87			12.97	
TP			13244.65			13457.81			14065.79			14077.77	
TPG			1500			1500			1500			1500	

and 57-bus systems and solved by using proposed OGSA, GSA, PSO, and GA successively. For strategic bidding of wind power in the market is permitted by modifying the demand and then by updating the bidding coefficients in agreement to new demand as suggested in [50]. On the basis on this approach, MCP is calculated at modified demand, i.e. actual demand minus wind power. In this work, the operational cost of the wind power generator is not considered as it is justifiable to deliberate their imbalance cost due to uncertainty associated with wind generation. This is measured by the two components of imbalance cost (overestimation and underestimation). This reflects on the net profit gained by wind PS by subtracting imbalance cost from their revenue. Here, the penalty coefficient associated with underestimation and reserve coefficient with overestimation taken as 50% of MCP and equal to MCP, respectively. The optimal strategic bidding results on the both standard test systems with the inclusion of wind power by using proposed OGSA, GSA, PSO, and GA are presented in Table 4.6 and Table 4.7, respectively. In both systems, OGSA performs better as compared with considered algorithms. For IEEE standard 30-bus system, the MCP, net profit for CPS, and WPS using OGSA are 12.80 \$/MW, \$4256.5, and \$250.3035, respectively. Moreover, the total obtained cost of wind power is \$414.6565 of bifurcated in overestimation cost \$42.2995 and underestimation cost \$372.3570 For IEEE standard 57-bus system, the MCP, net profit for CPS, and WPS using OGSA are 12.61 \$/MW, \$13417.84, and \$246.5881, respectively. Moreover, the total obtained cost of wind power is \$408.5014 of bifurcated in overestimation cost \$41.6716 and underestimation cost \$366.8298.

From Table 4.4, Table 4.5, Table 4.6 and Table 4.7, it can be noted that with the inclusion of wind power in IEEE standard 30-bus and 57-systems, the MCP gets reduced from 14.15 to 12.80 \$/MW in former and from 12.97 to 12.61 \$/MW in latter. Moreover, the net profit of CPS is also reduced significantly for both systems, which is caused by the lower value of MCP and generation of the conventional system. These results show that the inclusion of wind power has a substantial effect on the MCP, individual, and total generation dispatch for CPSs. Simultaneously, the lower value of MCP would satisfy all the purchase bids. The requirement of power dispatch from CPS in power system operation is reduced due to the inclusion of wind PS in the dispatching process. Moreover, the estimation of overestimation is very less as compared with underestimation uncertainties associated with wind power. Therefore, application of KDM in scenario reduction is better

TABLE 4.6: Optimum bidding results for IEEE standard 30-bus with amalgamation of wind power

PSs	$\alpha_{m,t}$	GA			PSO			GSA			OGSA		
		$\beta_{m,t}$	PG (MW)	Profit (\$)	$\beta_{m,t}$	PG (MW)	Profit (\$)	$\beta_{m,t}$	PG (MW)	Profit (\$)	$\beta_{m,t}$	PG (MW)	Profit (\$)
1	2.0	0.043369	160	1429.56	0.048167	160	1464.98	0.049575	160	1572.05	0.049242	160	1632.5
2	1.75	0.195359	63.36	549.71	0.197386	61.51	549.30	0.215113	59.69	574.8	0.189561	70.19	689.57
3	1.0	0.561368	32.04	273.38	0.596858	28.84	258.24	0.453362	35.26	325.15	0.647421	30.11	298.72
4	3.25	0.088848	100	745.08	0.084439	100	767.22	0.104385	97.96	818.8	0.109269	99.31	866.43
5	3.0	0.258245	46.32	341.72	0.230275	48.85	368.05	0.251243	47.57	391.8	0.303061	44.22	384.64
6	3.0	0.258245	46.32	341.72	0.230275	48.85	368.05	0.251243	47.57	391.8	0.303061	44.22	384.64
MCP			11.53			11.76			12.4253			12.80	
TP			3681.16			3775.86			4074.4			4256.5	
TPG			448.05			448.05			448.05			448.05	
W_g			51.95			51.95			51.95			51.95	
$O_c(w_g)$			38.1026			38.8627			41.0612			42.2995	
$U_c(w_g)$			335.4122			342.1030			361.4568			372.3570	
$IMC(Wg_n)$			373.5148			380.9656			402.5180			414.6565	
P_{WPS}			225.4687			229.9664			242.9763			250.3035	

TABLE 4.7: Optimum bidding results for both IEEE standard 57-bus with amalgamation of wind power

PSs	$\alpha_{m,t}$	GA			PSO			GSA			OGSA		
		$\beta_{m,t}$	PG (MW)	Profit ($)	$\beta_{m,t}$	PG (MW)	Profit ($)	$\beta_{m,t}$	PG (MW)	Profit ($)	$\beta_{m,t}$	PG (MW)	Profit ($)
1	1.7365	0.020926	481.97	4466.11	0.022242	460.78	4367.64	0.021140	503.25	4923.36	0.021315	510.02	5102.39
2	10	0.093054	19.58	31.85	0.085062	23.34	40.90	0.095375	24.9	52.94	0.118167	22.07	52.68
3	7.1429	0.055503	84.31	344.03	0.070490	68.70	299.17	0.089745	58.3	280.91	0.086831	62.94	315.82
4	10	0.093054	19.58	31.85	0.085062	23.34	40.90	0.095375	24.9	52.94	0.118167	22.07	52.68
5	1.81	0.021983	455.45	4186.68	0.020178	504.28	4573.59	0.021931	481.74	4671.9	0.023482	459.83	4584.5
6	10	0.093054	19.58	31.85	0.085062	23.24	40.90	0.09375	24.9	52.94	0.118167	22.07	52.68
7	2.4390	0.025527	367.57	3124.72	0.027791	344.26	344.26	0.030105	330.05	3017.93	0.029132	349.05	3257.04
MCP			11.82			11.99			12.38			12.61	
TP			12217.07			12459.12			13052.93			13417.84	
TPG			1448.05			1448.05			1448.05			1448.05	
W_g			51.95			51.95			51.95			51.95	
$O_c(w_g)$			39.0609			39.6227			40.9115			41.6716	
$U_c(w_g)$			343.8484			348.7938			360.1390			366.8298	
$IMC(Wg_n)$			382.9093			388.4165			401.0505			408.5014	
P_{WPS}			231.1397			234.4640			242.0905			246.5881	

in uncertainty modeling.

TABLE 4.8: Performance comparison of different approaches for both IEEE Standard 30-bus and IEEE 57-bus Systems

Total Profits ($)	IEEE 30-bus system				IEEE 57-bus system			
	GA	PSO	GSA	OGSA	GA	PSO	GSA	OGSA
Best ($)	4490.02	4672.93	5212.59	5317.719	13244.65	13457.81	14065.79	14077.77
Worst ($)	3941.41	4253.56	4798.86	4944.638	11448.63	12009	12982.51	13212.03
Mean	4187.19	4395.08	4944.70	5036.50	11927.7	12509.51	13446.45	13590.17
SD	155.87	124.91	109.75	94.66	415.5907	386.71	350.59	262.77

Furthermore, to establish the robustness of optimization methods, a comparative result of quality solutions of GA, PSO, GSA, and OGSA are presented in Table 4.8 of 20 independent trials with identical population size and maximum iteration to get the better measure of the algorithms. It can be observed from Table 8 that GSA is giving better results in terms of best, worst, mean, and SD. This establishes the robustness of proposed OGSA compared with GSA, PSO and GA.

4.7.2 CASE II

In this case, optimal strategic bidding model is considered for IEEE 30-bus and 57 bus systems respectively. The considered framework is utilized to obtain the maximum profit for power suppliers. The systems data are presented in Table A.1 and Table A.6 respectively. The proposed optimal bidding strategies with and without considering wind power on both systems are already investigated in CASE I. Further, the considered systems are modified to accommodate one solar power supplier to extent the influence of combined wind and solar source. One solar and wind supplier of each 200 MW rated capacity is assumed in this work. The suggested formulation is solved on a 3.20 GHz, $i5$ processor, 4GB RAM PC using the OGSA in MATLAB R2014a.

For the wind power estimation, compared to previous case I, in this case the planning period is considered as 1300–1400 hrs from 1 august to 31 August 2005 of Barnstable city, Massachusetts, USA [93]. The Air density and shear coefficient value are 1.242 kg/m3 and 0.35 respectively. The wind turbine VENSYS-100 and 2.5 MW capacity generator is located at 100-meter hub height (VENSYS Wind Turbines) are used to generate wind power. The wind speed data is fitted into a various probability distributions are shown in Figure 4.3.

The Log Likelihood, Mean, and Variance values are calculated using various distributions

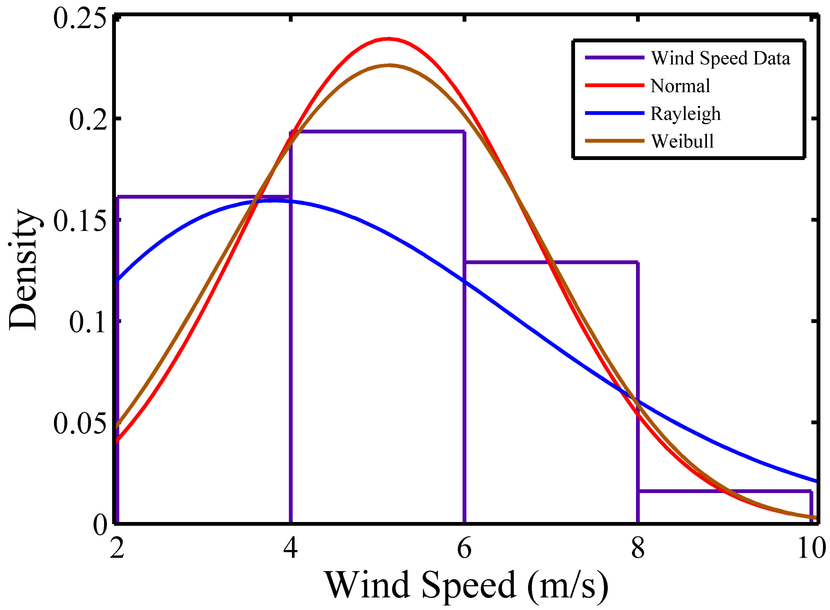


FIGURE 4.3: Curve fitting of the historical single hour (1300-1400 hrs) wind speed data of Barnstable city, MA, USA for different distributions

and are presented in Table 4.9. It should be noted that the log-likelihood value of Weibull distribution is better than others, indicating best fitting of the data in the distribution.

Shape and scale parameters values 3.34 and 7.93 m/s are calculated using (4.2) and (4.3) respectively. Then, a thousand wind speed scenarios are generated and convert into power scenarios using wind speed-power relationship. The each generated scenario assigned a probability of normalization obtained using Weibull distribution to make their summation equal to unity. The Weibull and normalize the density function of probabilities shown in

TABLE 4.9: Value of log likelihood, mean, and variance for the different distributions of historical wind speed data

	Normal Fit	Rayleigh Fit	Weibull Fit
Log Likelihood Value	-59.3305	-64.7905	-59.2297
Mean	5.12151	4.76584	5.12102
Variance	2.77917	6.20614	2.8617

Figure 4.4 for generated power scenarios.

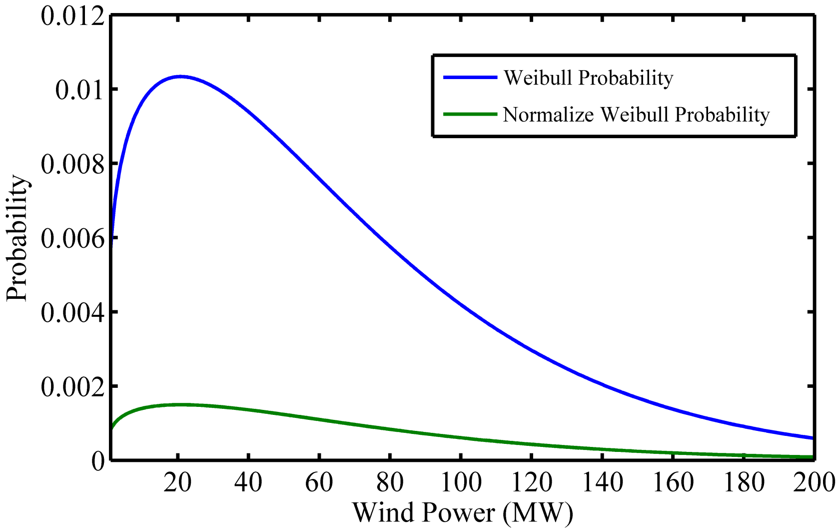


FIGURE 4.4: Weibull and normalise Weibull probability densities for generated power scenarios of single hour (1300-1400 hrs) wind speed data of Barnstable city, MA, USA

For the solar power estimation, single hour solar irradiation data from 1 January to 31 December 2013 of Barnstable city, Massachusetts, USA is taken as study [95]. Solar irradiation is converted in to solar power by using PV module specifications are taken from [87] and given in Table A.7. The solar irradiation data is fitted into a various probability distributions are shown in Figure 4.5.

The Log Likelihood, Mean, and Variance values are calculated using various distributions and are presented in Table 4.10. It should be noted that the log-likelihood value of Beta distribution is better than others, indicating best fitting of the data in the distribution.

The values of Beta distribution parameters A and B are 1.3909 and 1.2518 respectively for historical solar irradiation data and calculated by using equation (4.14) and (4.15) respectively. Then, a thousand solar irradiation scenarios are generated and convert into power scenarios using PV module specifications. The each generated scenario assigned a probability of normalization obtained using Beta distribution to make their summation

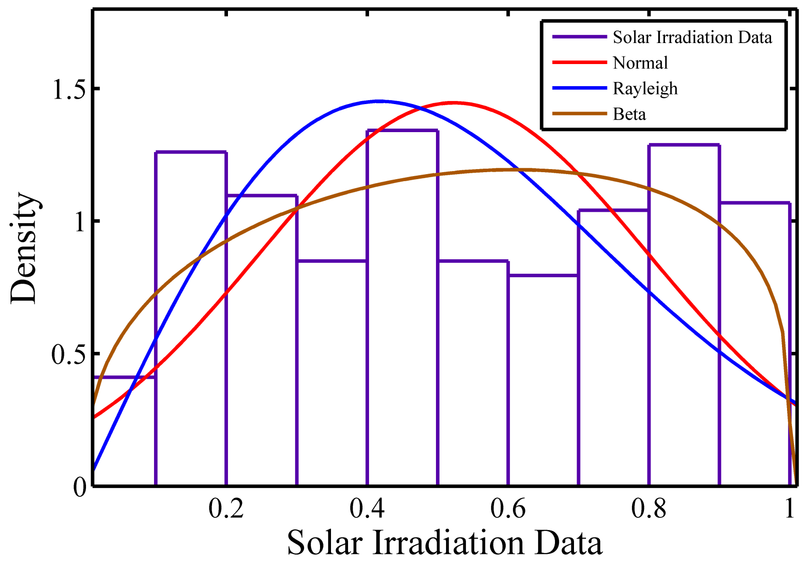


FIGURE 4.5: Curve fitting of the historical single hour (1300-1400 hrs) solar irradiaton data of Barnstable city, MA, USA for different distributions

TABLE 4.10: Value of log likelihood, mean, and variance for the different distributions of historical solar irradiation data

	Normal Fit	Rayleigh Fit	Weibull Fit
Log Likelihood Value	-47.2392	-34.9839	10.1446
Mean	0.52266	0.523565	0.526305
Variance	0.0760555	0.0749005	0.06844

equal to unity. The Beta and normalize the density function of probabilities shown in Figure 4.6 for generated power scenarios.

Since, the large number of scenarios predicts the uncertainty of wind and solar power. However, there are few scenarios exhibit same assessment. Therefore, KDM method is employed to eliminate such scenario for better modeling of wind power. Here, 10 reduced scenarios are generated using 1000 scenarios for wind and solar are given in Table 4.11 and Table 4.12 respectively. Based on the final obtained value of wind and solar power outputs and their corresponding probabilities, the expected values of wind and solar power are 49.54 MW and 73.29 MW respectively.

Thereafter, the proposed optimal bidding strategies is investigated with wind only, with solar only and with combined wind-solar using OGSA. The optimum value for coefficients of bidding of different CPS with wind only, with solar only and with combined wind-solar power using OGSA for both systems are given in Table 4.13 and Table 4.14, respectively. Effects of Renewable power sources are successively considered on both considered systems. For bidding strategy of wind power, the system operator is allow to modifying

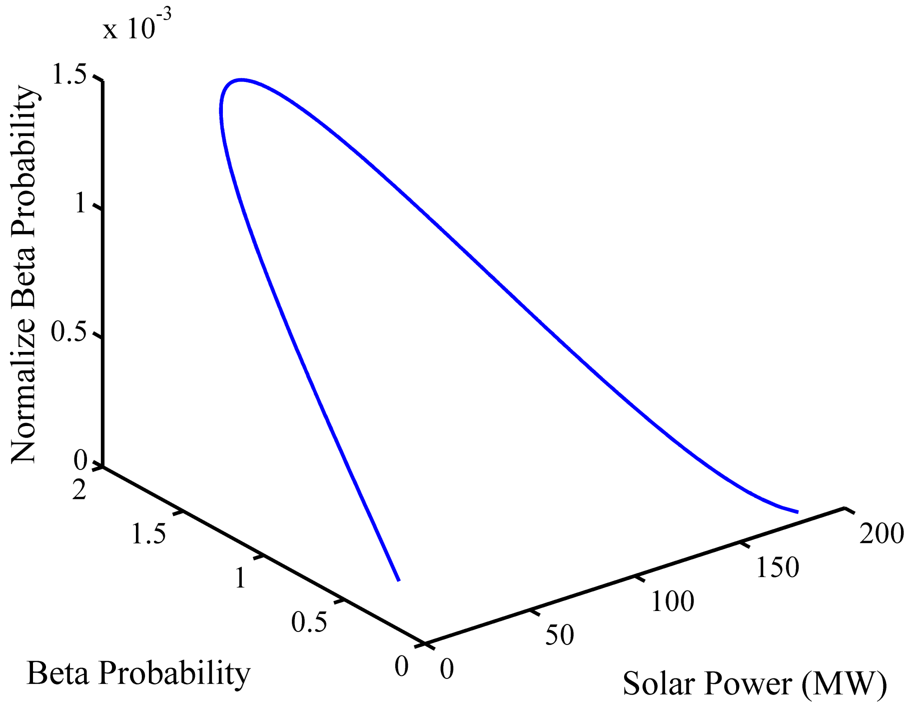


FIGURE 4.6: Beta and normalise Beta probability densities for generated power scenarios of single hour (1300-1400 hrs) wind speed data of Barnstable city, MA, USA

TABLE 4.11: Final KDM with wind power outputs and their probabilities for reduced ten numbers of scenarios

Index	1	2	3	4	5	6	7	8	9	10	W_a (MW)	Probability	Min (KD)
1	0	27.85	51.7	76.35	92.08	108.9	127.1	141.2	164.8	179.5	14.39	0.234229	27.85
2	27.85	0	23.85	48.5	64.23	81.06	99.26	113.4	136.9	151.6	42.24	0.443626	23.85
3	51.70	23.85	0	24.65	40.37	57.21	75.41	89.52	113.1	127.8	66.09	0.17126	23.85
4	76.35	48.5	24.65	0	15.73	32.56	50.76	64.87	88.43	103.1	90.74	0.080668	15.73
5	92.08	64.23	40.37	15.73	0	16.84	35.04	49.15	72.71	87.40	106.5	0.025689	15.73
6	108.9	81.06	57.21	32.56	16.84	0	18.20	32.31	55.87	70.56	123.3	0.025047	16.84
7	127.1	99.26	75.41	50.76	35.04	18.20	0	14.11	37.67	52.36	141.5	0.011009	14.11
8	141.2	113.4	89.52	64.87	49.15	32.31	14.11	0	23.56	38.25	155.6	0.005085	14.11
9	164.8	136.9	113.1	88.43	72.71	55.87	37.67	23.56	0	14.69	179.2	0.002536	14.69
10	179.5	151.6	127.8	103.1	87.39	70.56	52.36	38.25	14.69	0	193.9	0.000852	14.69

TABLE 4.12: Final KDM with solar power outputs and their probabilities for reduced ten numbers of scenarios

Index	1	2	3	4	5	6	7	8	9	10	W_a (MW)	Probability	Min (KD)
1	0	11.42	34.23	46.35	62.47	80.47	98.7	114.8	131.1	150.2	16	0.022218	11.42
2	11.42	0	22.81	34.93	51.05	69.31	87.28	103.4	119.7	138.8	27.42	0.075345	11.42
3	34.23	22.81	0	12.12	28.24	46.5	64.47	80.60	96.85	116	50.23	0.268311	12.12
4	46.35	34.93	12.12	0	16.12	34.38	52.35	68.49	84.73	103.9	62.35	0.163971	12.12
5	62.47	51.05	28.24	16.12	0	18.27	36.23	52.37	68.62	87.76	78.47	0.277874	16.12
6	80.73	69.31	46.50	34.38	18.27	0	17.97	34.1	50.35	69.49	96.74	0.09117	17.97
7	98.7	87.28	64.47	52.35	36.23	17.97	0	16.13	32.38	51.53	114.7	0.046975	16.13
8	114.8	103.4	80.6	68.49	52.37	34.10	16.13	0	16.25	35.39	130.8	0.042748	16.13
9	131.1	119.7	96.85	84.73	68.62	50.35	32.38	16.25	0	19.14	147.1	0.00999	16.25
10	150.2	138.8	116	103.9	87.76	69.49	51.53	35.39	19.14	0	166.2	0.001399	19.14

the existing demand, which means actual demand excluding wind power generation, and then updates the bidding coefficients in accordance with the changing demand [50]. Based on this approach wind and solar power are considered to determine the new MCP. First the wind power generator is considered and new value of MCP is calculated by updating the bidding coefficients at modified demand. Similarly, MCP with the inclusion of solar power and finally, the aggregate benefits of wind and solar generator are considered. In this analysis, the consideration of operating cost for both the renewable sources has not been taken into account. However, due to the associated intermittency of these renewable sources it is acceptable to consider their imbalance cost. This cost is determined in terms of overestimation and underestimation of generation from both solar and wind. And the effect of this cost is reflected on total profit obtained by renewable suppliers in terms of revenue minus the imbalance cost. Also, the penalty coefficient and reserve coefficient linked with underestimation and overestimation separately are considered as 50% of MCP and equivalent to MCP respectively. The results of proposed bidding strategy on considered systems with only wind, with only solar and with combined wind-solar by using OGSA are presented in Table 4.13 and Table 4.14, respectively.

It is observed that from the case I Table 4.4, the market is cleared at MCP value of 14.15

TABLE 4.13: Optimum bidding results for IEEE 30-bus with amalgamation of wind and solar power

PSs	$\alpha_{m,t}$	with wind only			with solar only			with both wind and solar		
		$\beta_{m,t}$	PG (MW)	Profit ($)	$\beta_{m,t}$	PG (MW)	Profit ($)	$\beta_{m,t}$	PG (MW)	Profit ($)
1	2.0	0.049984	160	1661.96	0.049886	160	1570.03	0.050156	160	432.87
2	1.75	0.223528	64.70	653.79	0.208066	60.99	585.25	0.229582	48.81	436.93
3	1.0	0.680919	32.03	319.85	0.747376	25.02	246.39	0.66874	21.89	201.09
4	3.25	0099466	100	890.32	0.108838	93.93	787.09	0.109776	81.76	623.31
5	3.0	0.307913	46.86	413.13	0.279827	43.38	361.31	0.325901	32.35	250.64
6	3.0	0.307913	46.86	413.13	0.279827	43.38	361.31	0.325901	32.35	250.64
MCP ($/MW)		12.99			12.41			11.56		
TCPS ($)		4352.19			3911.38			3195.48		
TPG-CPS (MW)		450.46			426.71			377.17		
RPG (MW)		49.5406			73.2897			49.5406 (W), 73.2897 (S)		
OCRs ($)		46.7718			119.1724			41.6230(W), 111.0099(S)		
UCRs ($)		368.7903			257.9840			328.1921(W), 240.3139(S)		
IMCRs ($)		415.5621			377.1564			369.8151(W), 351.3238(S)		
PRs ($)		227.9703			532.3688			202.8742(W), 495.9051(S)		

$/MW, total generation of CPS is 500 MW and net profit is $5317.72 with IEEE standard 30 bus system without considering wind and solar power. But if only wind power is included with CPS then MCP is reduced to 12.99 $/MW and total generation of CPS is reduced to 450.46 MW. In addition, CPS' net profit is also significantly reduced by $4352.19, which is caused by the lower value of MCP and conventional system generation. The wind power net profit, overestimation and underestimation costs are $227.9703, $46.7718 and

$368.7903 respectively. In the second case i.e. only solar power with CPS, the net profit value, overestimation and underestimation costs are 532.3688, $119.1724, and $257.9840 respectively. For this case, the MCP value is 12.41 $/MW with total generation of CPS 426.71 MW which is lower than conventional and wind due to significant power generation from the solar. Finally, when both the wind and solar are considered with CPS, MCP is 11.56 $/MW, which is lowest among all previous considered cases.

Similarly, From Table 4.5, it is observed that the market is cleared at MCP value of 12.97

TABLE 4.14: Optimum bidding results for IEEE 57-bus with amalgamation of wind and solar power

		with wind only			with solar only			with both wind and solar		
PSs	$\alpha_{m,t}$	$\beta_{m,t}$	PG (MW)	Profit ($)	$\beta_{m,t}$	PG (MW)	Profit ($)	$\beta_{m,t}$	PG (MW)	Profit ($)
1	1.7365	0.021880	501.65	5078.29	0.022239	485.76	4846.56	0.022531	466.59	4535.04
2	10	0.123756	21.92	54.65	0.076760	33.08	73.07	0.094126	23.9	48.04
3	7.1429	0.071514	77.88	390.7	0.088860	60.73	301.56	0.076142	67.06	310.52
4	10	0.123756	21.92	54.65	0.076760	33.08	73.07	0.094126	23.9	48.04
5	1.81	0.023322	467.47	4703.2	0.023240	461.68	4569.9	0.024014	434.71	4197.96
6	10	0.123756	21.92	54.65	0.076760	33.08	73.07	0.094126	23.9	48.04
7	2.4390	0.030421	337.71	3195.7	0.031635	319.29	2980.3	0.029101	337.11	3034.43
MCP ($/MW)		12.71			12.54			12.25		
TCPS ($)		13531.86			12917.50			12222.07		
TPG-CPS (MW)		1450.46			1426.7103			1377.1697		
RPG (MW)		49.5406			73.2897			49.5406 (W), 73.2897 (S)		
OCRs ($)		45.7637			120.4208			44.1074(W), 117.6360(S)		
UCRs ($)		360.8410			260.6865			347.7815(W), 254.6578(S)		
IMCRs ($)		406.6047			381.1073			391.8888(W), 372.2938(S)		
PRs ($)		223.0564			537.9455			214.9835(W), 525.5050(S)		

$/MW, total generation of CPS is 1500 MW and net profit is $14077.77. But if only wind power is included with CPS then MCP is reduced to 12.71 $/MW and total generation of CPS is reduced to 1450.46 MW. In addition, CPS net profit is also significantly reduced by $1426.7103, which is caused by the lower value of MCP and conventional system generation. The wind power net profit, overestimation and underestimation costs are $223.0564, $45.7637 and $360.8410 respectively. In the second case i.e. only solar power with CPS, the net profit value, overestimation and underestimation costs are $537.9455, $120.4208, and $260.6865 respectively. For this case, the MCP value is 12.54 $/MW with total generation of CPS 1426.7103 MW which is lower than conventional and wind due to significant power generation from the solar. Finally, when both the wind and solar are considered with CPS, MCP is 12.25 $/MW, which is lowest among all previous considered cases.

From Table 4.13 and Table 4.14, it can be observed that all the purchase bids would satisfy by the lower MCP value. Due to the presence of solar and wind suppliers in the process of dispatch, there will be fewer CPS requirements in power system operation. Further, the overestimation estimate is very small compared to the underestimation of solar and wind power uncertainties. Therefore, applying KDM in reduction of scenarios is better in modeling uncertainty. This will encourage to the solar and wind power suppliers for bidding the extra power into the real-time market if the underestimation is positive.

4.7.3 CASE III

In this case, the double sided optimal strategic bidding model is analytically tested on IEEE 30-bus system, and the system data for suppliers and large buyers is presented in Table A.5. The system consist of six conventional power suppliers (CPS) and two large consumers. Also, the value of constant load demand is 300 MW with load price elasticity (k=5) at the time of bidding for IEEE 30-bus system. The proposed framework is utilized to obtain the maximum profit for power suppliers and large buyers. The proposed optimal bidding strategies without considering wind and solar power on system is already investigated in Chapter 3, CASE III. Further, the considered model is modified to accommodate one solar and one wind power supplier to the extent the influence of solar and wind source. In this work, one supplier of wind and solar of each rated capacity of 200 MW are considered. The proposed model has beeen framed as a multi-objective optimization problem and solved by using TOPSIS amalgamation with OGSA (TOGSA) in MATLAB R2014a on a 3.20 GHz, i5 processor, 4GB RAM PC.
For the wind power estimation, single hour wind speed data from 1 August to 31 August 2005 of Barnstable city, Massachusetts, USA [93]. The air density and shear coefficient value are 1.242 kg/m^3 and 0.35 respectively. The wind turbine VENSYS-100 and 2.5 MW capacity generator located at 100-meter hub height are used to generate wind power. The wind speed data is fitted into various probability distributions are shown in Figure 4.7. The values of log likelihood, mean and variance are calculated using various distributions and are presented in Table 4.15. It should be noted that the log-likelihood value of Weibull distribution is better than others, indicating best fitting of the data in the distribution.

The values of shape and scale parameters calculated using (4.2) and (4.3) are 3.3094

Table 4.15: Value of log likelihood, mean, and variance for the different distributions of historical wind speed data

	Normal Fit	Rayleigh Fit	Weibull Fit
Log Likelihood Value	-60.742	-65.6732	-60.4794
Mean	5.20054	4.85338	5.20428
Variance	3.04414	6.43624	2.99978

and 8.0654 m/s respectively. Then, a thousand wind speed scenarios are generated and converted into power scenarios using wind speed-power relationship. A normalization

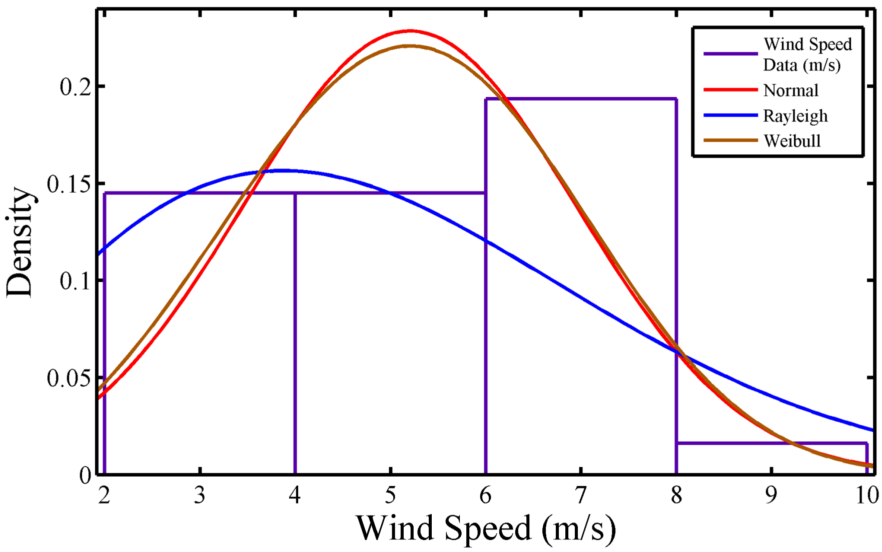


FIGURE 4.7: Curve fitting of the historical single hour (1400-1500 hrs) wind speed data of Barnstable city, MA, USA for different distributions

probability obtained using Weibull distribution is assigned to each generated scenario so that their summation becomes equal to unity. The Weibull and normalize density function of probabilities shown in Figure 4.8 for generated power scenarios.

For the solar power estimation, single hour solar irradiation data from 1 January to 31 December 2013 of Barnstable city, Massachusetts, USA [95]. Solar irradiation is converted into solar power by using PV module specifications given in Table A.7. The solar irradiation data fitted into various probability distributions are shown in Figure 4.9.

The values of log likelihood, mean, and variance are calculated using various distributions and are presented in Table 4.16. It should be noted that the log-likelihood value of Beta distribution is better than others, indicating best fitting of the data in the distribution.

The values of Beta distribution parameters A and B are 1.3732 and 1.3180 respectively

TABLE 4.16: Value of log likelihood, mean, and variance for the different distributions of historical solar irradiation data

	Normal Fit	Rayleigh Fit	Weibull Fit
Log Likelihood Value	-47.6376	-33.1864	10.1381
Mean	0.507468	0.51182	0.510256
Variance	0.0762217	0.0715777	0.0677011

for historical solar irradiation data and calculated by using equation (4.14) and (4.15) respectively. Then, a thousand solar irradiation scenarios are generated and converted into power scenarios using PV module specifications. A normalization probability obtained

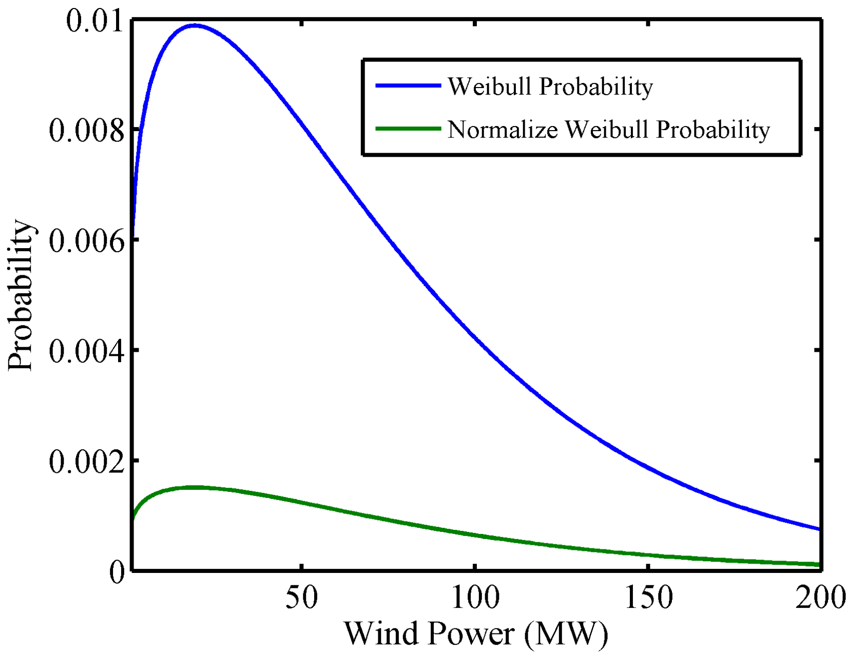


FIGURE 4.8: Weibull and normalise Weibull probability densities for generated power scenarios of single hour (1400-1500 hrs) wind speed data of Barnstable city, MA, USA

using Beta distribution is assigned to each generated scenario so that their summation becomes equal to unity. The Beta and Normalize density function of probabilities shown in Figure 4.10 for generated power scenarios.

Since, the large number of scenarios predicts the uncertainty of wind and solar power. However, there are few scenarios exhibiting the same assessment. Therefore, KDM method is employed to eliminate such scenario for better modeling of wind power. Here, 10 reduced scenarios generated using 1000 scenarios for wind and solar are given in Table 4.17 and Table 4.18, respectively. Based on the final obtained value of wind and solar power outputs and their corresponding probabilities, the expected values of wind and solar power are 50.31 MW and 70.76 MW respectively.

The optimal double sided strategic bidding model is framed as a multi objective optimization problem and tested on considered system in Chapter 3, case III. Results for the considered system show that the proposed technique TOGSA is more suitable as compared to GSA and MC. Therefore, in this case modified test system is considered with wind power only, with solar only and with combined wind-solar and solved by using TOGSA. Renewable based power sources in the modified system are successively considered to measure the effect of renewable. System operators are allowed to modify existing demand that means actual demand excluding generation from wind power for strategic bidding of wind power on the emerging power market, system operator is permitted to modify the existing

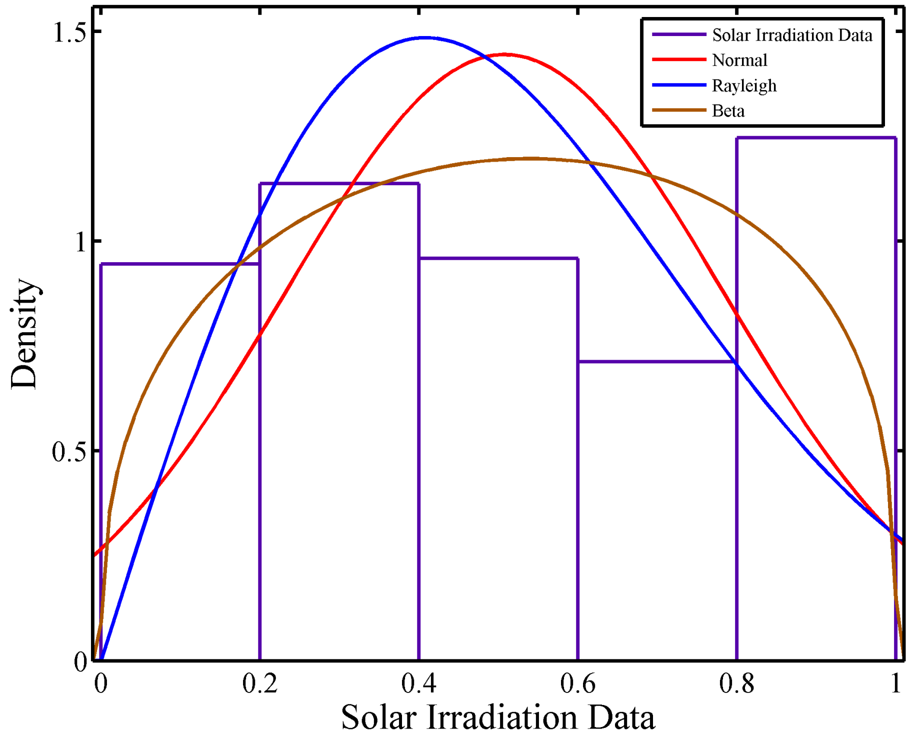


FIGURE 4.9: Curve fitting of the historical single hour (1400-1500 hrs) solar irradiation data of Barnstable city, MA, USA for different distributions

TABLE 4.17: Final KDM with wind power outputs and their probabilities for reduced ten numbers of scenarios

Index	1	2	3	4	5	6	7	8	9	10	W_a (MW)	Probability	Min (KD)
1	0	17.39	45.38	63.97	79.87	97.11	121.5	136.3	150.2	165.5	29.22	0.546236	17.39
2	17.39	0	27.99	46.58	62.48	79.72	104.1	118.9	132.8	148.1	46.62	0.181994	17.39
3	45.38	27.99	0	18.59	34.49	51.73	76.12	90.90	104.8	120.1	74.61	0.105963	18.59
4	63.97	46.58	18.59	0	15.9	33.14	57.53	72.31	86.24	101.5	93.2	0.087006	15.9
5	79.87	62.48	34.49	15.9	0	17.24	41.63	56.41	70.34	85.62	109.1	0.037677	15.9
6	97.11	79.72	51.73	33.14	17.24	0	24.39	39.17	53.1	68.38	126.3	0.026649	17.24
7	121.5	104.1	76.12	57.53	41.63	24.39	0	14.78	28.71	43.99	150.7	0.004927	14.78
8	136.3	118.9	90.9	72.31	56.41	39.17	14.78	0	13.93	29.21	165.5	0.006487	13.93
9	150.2	132.8	104.8	86.24	70.34	53.1	28.71	13.93	0	15.28	179.4	0.002440	13.93
10	165.5	148.1	120.1	101.5	85.62	68.38	43.99	29.21	15.28	0	194.7	0.000622	15.28

demand and then updating the coefficients of bidding in agreement with the modifying demand. Based on this approach wind and solar power are considered to determine the new MCP. First the wind power generator is considered and new value of MCP is calculated by updating the bidding coefficients at modified demand. Similarly, MCP with the inclusion of solar power and finally, the aggregate benefits of wind and solar generator are considered. In this analysis, the consideration of operating cost for both the renewable sources has not been taken into account. However, due to the associated intermittency of

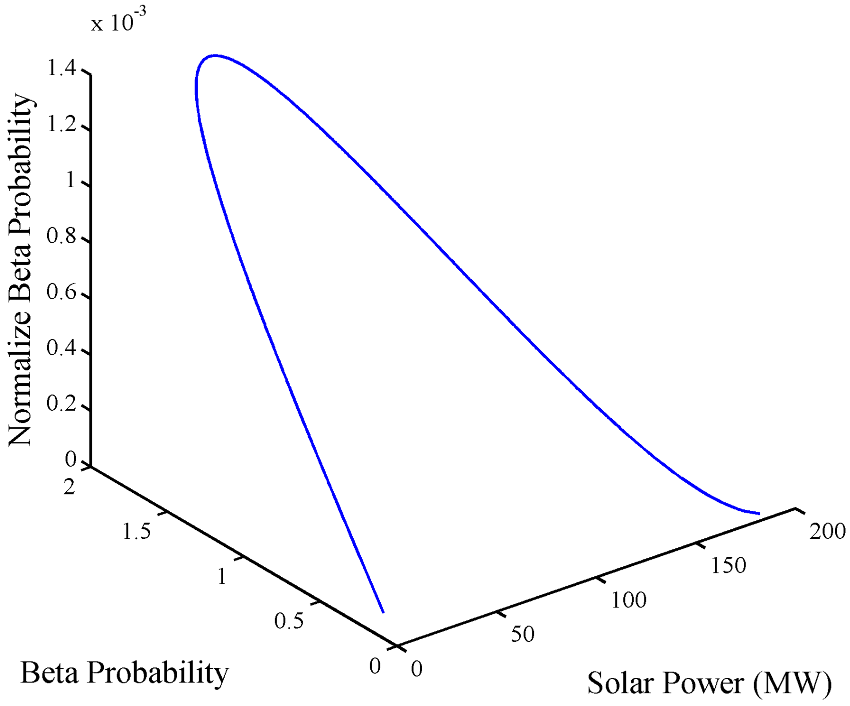


FIGURE 4.10: Beta and normalize Beta probability densities for generated power scenarios of single hour (1400-1500 hrs) wind speed data of Barnstable city, MA, USA

TABLE 4.18: Final KDM with solar power outputs and their probabilities for reduced ten numbers of scenarios

Index	1	2	3	4	5	6	7	8	9	10	W_a (MW)	Probability	Min (KD)
1	0	14.01	41.31	65.74	82.84	99.31	109.9	127.2	138.5	154	12.44	0.009583	14.01
2	14.01	0	27.3	51.73	68.83	85.29	95.89	113.21	124.46	140	26.46	0.067130	14.01
3	41.31	27.3	0	24.43	41.54	58	68.59	85.91	97.17	112.71	53.75	0.450183	24.43
4	65.74	51.73	24.43	0	17.11	33.57	44.16	61.48	72.74	88.28	78.18	0.208449	17.11
5	82.84	68.83	41.54	17.11	0	16.46	27.06	44.38	55.63	71.17	95.29	0.130413	16.46
6	99.31	85.29	58	33.57	16.46	0	10.59	27.91	39.17	54.71	111.7	0.082165	10.59
7	109.9	95.89	68.59	44.16	27.06	10.59	0	17.32	28.58	44.11	122.3	0.032668	10.59
8	127.2	113.2	85.91	61.48	44.38	27.91	17.32	0	11.26	26.80	139.7	0.015613	11.26
9	138.5	124.5	97.17	72.74	55.63	39.17	28.58	11.26	0	15.54	150.9	0.003062	11.26
10	154	140	112.7	88.28	71.17	54.71	44.11	26.80	15.54	0	166.5	0.000735	15.54

these renewable sources it is acceptable to consider their imbalance cost. This cost is determined in terms of overestimation and underestimation of generation for both solar and wind. And the effect of this cost is reflected on the net profit obtained by renewable power suppliers in terms of revenue minus the imbalance cost. Also, the penalty coefficient and reserve coefficient linked with underestimation and overestimation separately are taken as 50% of MCP and equal to MCP respectively. The optimal double sided strategic bidding results on modified test system with wind power only, with solar power only and with combined wind-solar power by using TOGSA are given in Table 4.19.

TABLE 4.19: Optimum bidding results for IEEE 30-bus with amalgamation of wind and solar power

		with wind only			with solar only			with both wind and solar		
PSs	$\alpha_{m,t}$	$\beta_{m,t}$	PG (MW)	Profit ($)	$\beta_{m,t}$	PG (MW)	Profit ($)	$\beta_{m,t}$	PG (MW)	Profit ($)
1	6.0	0.074476	145.76	1260.40	0.032677	160	1323.61	0.024928	160	1278.21
2	5.25	0.130126	92.46	571.64	0.154422	97.53	556.14	0.428093	55.63	423.80
3	3.0	0.949644	27.64	262.20	0.52532	52.33	307.55	0.837573	45.63	297.26
4	9.75	0.039809	120	419.81	0.202882	58.61	283.58	0.094028	89.85	338.18
5	9.0	0.207086	42.83	174.51	0.488099	47.44	166.73	0.899081	45.63	153.61
6	9.0	0.207086	42.83	174.51	0.488099	47.44	166.73	0.899081	45.63	153.61
Total			471.51	2863.07		463.36	2804.34		442.37	2644.68
LBs	$\phi_{n,t}$	$\varphi_{n,t}$	CD (MW)	Benefit ($)	$\varphi_{n,t}$	CD (MW)	Benefit ($)	$\varphi_{n,t}$	CD (MW)	Benefit ($)
1	30	0.073966	185.40	1167.50	0.081677	170.52	1211.82	0.073867	192.39	1253.54
2	25	0.073931	117.86	610.20	0.062013	143.96	663.46	0.041960	150	706.68
Total			303.25	1777.7		314.48	1875.28		342.39	1960.22
MCP ($/MW)			16.29			16.07			15.79	
Q(MCP) (MW)			218.57			219.64			221.06	
TPT(MW)			521.57			534.12			563.45	
RPG (MW)			50.31			70.76			50.31(W), 70.76(S)	
OCRs ($)			58.6422			153.55			56.84(W), 150.88(S)	
UCRs ($)			468.20			328.20			453.83(W), 322.48(S)	
IMCRs ($)			526.84			481.75			510.67(W), 473.36(S)	
PRs ($)			292.71			655.36			283.72(W), 643.94(S)	

From Table 3.8, it is observed that from the Chapter 3 in case III, the market is cleared at MCP value of 16.50 $/MW, total generation of CPS is 520.2 MW, total demand of large consumers is 302.7 MW, total power traded is 520.2 MW, and net profit for CPS and large consumers are $3140.4 and $1729.1 respectively. From Table 4.19, it is observed that when only wind power is included with CPS then MCP is reduced to 16.29 $/MW, total generation of CPS is reduced to 471.51 MW, total demand of large consumers and total traded power are increased to 303.25 MW and 521.57 MW respectively, and the net profit of CPS is reduced to $2863.07 which is caused by the lower value of MCP and generation of CPS. Moreover, the net profit of large consumers is increased significantly, which is caused by the lower value of MCP and higher demand of large consumers. The wind power net profit, overestimation and underestimation costs are $292.71, $58.64 and $468.20 respectively. In the second case i.e. only solar power with CPS, the net profit value, overestimation and underestimation costs are $655.36, $153.55, and $328.20 respectively. For this case, the MCP value is 16.07 $/MW, total generation of CPS 463.36 MW which is lower than conventional and wind due to significant power generation from the solar, total demand of large consumers and total traded power are increased to 314.48 MW and 534.12 respectively. Finally, when both the wind and solar are considered with CPS, MCP is 15.79 $/MW, which is lowest among all previous considered cases. From the obtained results, it can be observed that, due to the lower MCP value large number of customers gets attracted to buy more power which results in increased total power trade and finally satisfying all the purchase bids. Also, due to the integration of solar and wind power suppliers in the system the requirement of supply from CPS is highly reduced. Further, with the involvement of KDM, overestimation of uncertainty is very less as compared to the underestimation in both the solar and wind power generation. This will encourage the solar and wind power suppliers for bidding the extra power into the real-time market if the underestimation is positive.

4.8 Conclusions

In this section, single sided and double sided bidding strategy with inclusion of renewable energy sources have been evaluated to maximize profit of different market entities. A heuristic technique, OGSA is used to solve single sided bidding strategy and TOGSA is used to solve double sided bidding strategy. Wind speed and solar irradiation uncertainties are handled respectively by Weibull and Beta distribution of probability, and transformed into wind and solar power. Further, KDM method is used to reduce the samples of wind and solar power. In addition, the renewable energy variability is measured in terms of overestimation and underestimation. Furthermore, the uncertainty of the behaviour of rival is minimized using the function of Normal distribution of probability. It is found that from the obtained results, OGSA and TOGSA approaches are effective and promising to obtain the most compromising solutions. Amalgamations of wind and solar power also affects the bid as it reduces the CPS generation and provides less MCP value that would deliver sufficient electricity from accepted sales bids to meet all accepted purchase bids and increase the total traded power. Further, with the involvement of KDM, overestimation of uncertainty is very less as compared to the underestimation in both the solar and wind power generation. This will encourage the solar and wind power suppliers for bidding the extra power into the real-time market if the underestimation is positive. Results for the IEEE standard 30-bus and modified six supplier with two large buyers systems shows that the proposed techniques in this chapter are more suitable to obtain the most compromising solution for single and multi-objective strategic bidding problems of market participants.

In the next Chapter, the optimal coordinated bidding strategy between energy and reserve markets for profit maximization of power suppliers has been examined using proposed

OGSA in single side trading mechanism. And its performance has been evaluated and compared with the available literature.

Chapter 5

Coordinating Bidding Strategy between Energy and Reserve Markets

5.1 Introduction

Deregulation process includes un-bundling of electric power generation from the transmission system, which increases the requirements of ancillary services [96]. The ancillary services are separated into various services such as spinning and non spinning reserves, replacement reserves, Automatic Generation Control (AGC), black start, and voltage support. The ISO can procure the first four services by means of a daily competitive auction, whereas the last two services are more suitable for long-term purchases. The primary function of ancillary services are providing backup to power transmission network from the power supplier to the buyer. These services are essential to confirm that the market operators are capable of meeting their responsibilities [97]. Although, the objective of specific ancillary service spinning reserve is to maintain a balance between power supply and demand. Spinning reserve is an online generator's ability to increase and decrease its output in a short time. The main requirement of the spinning reserve is to maintain reliability of the system [5]. In this chapter, GENCOs are assumed to participate in the energy markets as well as in the reserve markets for ancillary services (only spinning reserves). In this context, OGSA is employed to pick optimal bidding strategy for GENCO's between the sets of discrete bids.

5.2 Market Clearing Mechanism in Energy and Spinning Reserve Markets

In some market structures of electric power such as CAISO wholesale market, the independent system operator (ISO) and the power exchange (PX) are separate bodies, in which, the PX manages the market of energy, and the ISO manages the market of spinning reserve [5]. In this type of market structures, market participants may elect themself or may select ISO on their behalf for buying required spinning reserve that is assisting in maintaining their energy requirements. Based on the forecasted conditions of the system and submitted plans from the scheduling coordinators (SCs) and PX , ISO first decides the necessities for an extra spinning reserve of each case beyond those already provided by the PX and the SCs as self-provision [98]. After this, ISO chooses and expenses the most low-budget services from submitted bids of spinning reserve. For this reason, besides bidding within the energy market, every power provider may have an enthusiasm for building up a strategic bidding in the market of reserve too, with the goal of maximizing its total profit. Hence, to attain the objective of total profit maximization, every power provider appearances a decision-making issue on how to construct optimally coordinated bidding strategy in electricity and spinning reserve markets.

5.2.1 Modeling of the PX

The main purpose of the PX is to manage the day-ahead energy market. After receiving a bid from the power suppliers using the transparent dispatch procedures, PX sets the generation output of active power that meets the total demand of the system. It is assumed that each power supplier is required to submit a non-decreasing linear energy supply bid function to the PX. Then PX determines a set of all suppliers generation outputs by solving the following problem if only load flow (5.1) and output limit (5.2) constraints are considered.

$$\alpha_m + \beta_m P_m^e = R_e \tag{5.1}$$

$$\sum_{m=1}^{CPS} P_m^e = D_e \tag{5.2}$$

$$P_{\min,m}^e \leq P_m^e \leq P_{\max,m}^e \tag{5.3}$$

The solution of (5.1) and (5.2) are taken wihout considering (5.3). Hence, the solution of (5.1) and (5.2) can be written as:

$$R_e = \frac{D_e + \sum\limits_{m=1}^{CPS} \frac{\alpha_m}{\beta_m}}{\sum\limits_{m=1}^{CPS} \frac{1}{\beta_m}} \tag{5.4}$$

$$P_m^e = \frac{R_e - \alpha_m}{\beta_m} \tag{5.5}$$

5.2.2 Modeling of the ISO

ISO managed spinning reserve in the ancillary services market. After receiving a bid of spinning reserve from the power suppliers using the transparent dispatch procedures, ISO sets the dispatch of spinning reserve of all suppliers such that it meets the total capacity of required spinning reserve of the system. It is assumed that each power supplier is required to submit a non-decreasing linear spinning reserve supply bid function to the ISO. ISO ensures that (5.6) to (5.8) must satisfy the dispatch of the spinning reserve when the security constraints (5.7) and reliability constraints (5.8) are considered.

$$\psi_m + \xi_m P_m^{sr} = R_{sr} \tag{5.6}$$

$$\sum_{m=1}^{CPS} P_m^{sr} = D_{sr} \tag{5.7}$$

$$P_{\min,m}^{sr} \leq P_m^{sr} \leq P_{\min,m}^{sr} \tag{5.8}$$

The solution of equation (5.6) and (5.7) are presented, when (5.8) is ignored,

$$R_{sr} = \frac{D_{sr} + \sum\limits_{m=1}^{CPS} \frac{\psi_m}{\xi_m}}{\sum\limits_{m=1}^{CPS} \frac{1}{\xi_m}} \tag{5.9}$$

$$P_m^{sr} = \frac{R_{sr} - \psi_m}{\xi_m} \tag{5.10}$$

5.3 Problem Formulation of Coordinating Bidding Strategy between Energy And Reserve Markets for Profit Maximization of the Power Suppliers

Optimally coordinating bidding problem in energy and spinning reserve market for m^{th} power supplier profit maximization can be described as

Maximize

$$F(\alpha_m, \beta_m, \psi_m, \xi_m) = R_e \times P_m^e + R_{sr} \times P_m^{sr} - C_m(P_m^e + P_m^n) \tag{5.11}$$

Subject to: Equation (5.1)-(5.3), (5.6)-(5.8) and

$$P_{\min,m}^e \leq P_m^e \leq P_{\min,m}^e - P_m^{sr} \tag{5.12}$$

Where $C_m(P_m^e + P_m^n)$ is the combined production cost of energy and reserve that is

$$C_m(P_m^e + P_m^n) = a_m(P_m^e + P_m^n) + b_m(P_m^e + P_m^n)^2 \tag{5.13}$$

Generally, at the time of operation, actual amount of the spinning reserve is less than the contracted amount utilized by the ISO. It is supposed that the capacity taken from the individual power supplier will be proportional to the contracted capacity [99]. Further, it has been assumed that a supplier is paid the price at MCP according to (5.9) for maintaining contracted spinning reserves of (5.10) irrespective of its utilization as defined in (5.11). Therefore, each supplier is required to determine the amount of consumed spinning reserve considering all costs involved in its spinning reserve bid. Hence, the part of spinning reserve consumed from its actual amount contracted with ISO is expressed as

$$P_m^n = P_m^{sr} \times \left({d_s^m}/{D_{sr}} \right) = P_m^{sr} \times K_m \tag{5.14}$$

As the amount of spinning reserve consumed is unknown in advance, ISO repeatedly conveys its requirement to power producers in real-time. This information help the producers to approximate their spinning reserve capacity on the basis of prior knowledge and tendency to take risks. The possibility of selection of a producer's bid is reduced if it overestimates this capacity and offers a costly bid. The bidding coefficients of energy and reserve follows a normal joint PDF. Normal joint PDF of energy bidding coefficients (α_m, β_m) are explained in chapter 3. Similarly, normal joint PDF [64] of reserve bidding coefficients

(ψ_m, ξ_m) are

$$(\psi_m, \xi_m)_j \sim N\left\{\begin{bmatrix} \mu_m^{(\psi)} \\ \mu_m^{(\psi)} \end{bmatrix}, \begin{bmatrix} \left(\sigma_m^{(\psi)}\right)^2 & \gamma_m \sigma_m^{(\psi)} \sigma_m^{(\xi)} \\ \gamma_m \sigma_m^{(\psi)} \sigma_m^{(\xi)} & \left(\sigma_m^{(\xi)}\right)^2 \end{bmatrix}\right\} \tag{5.15}$$

5.4 Solution Procedure of OGSA Applied to Coordinated Bidding Strategy Problem between Energy and Reserve Market

1. Set input data of considered test system for power suppliers bidding strategy in energy and reserve market. Also, set the parameters of the proposed OGSA.

2. Set population size (N) and randomly generate initial population λ for bidding coefficient $\beta_{m,t}$ of power suppliers in the decided search space of the problem.

3. Determine the market clearing price in energy market as (5.4) and in reserve market as (5.9). Also, determine the dispatch of each generator in energy market as (5.5) and in reserve market as (5.10) respectively.

4. Set power generation limits as (5.3) and reserve limits as (5.8) and balance the system load in both markets.

5. Determine actual utilized reserve quantity as (5.14) than calculate profit of each power supplier as (5.11).

6. Generate opposite population $(O\lambda)$ to the initial generated population (λ) in search space. Then determine the market clearing price in energy market as (5.4) and in reserve market as (5.9). Also, determine the dispatch of each generator in energy market as (5.5) and in reserve market as (5.10) respectively.

7. Set power generation limits as (5.3) and reserve limits as (5.8) and balance the system load in both markets.

8. Evaluate the fitness function for all random (λ) and opposite $(O\lambda)$ population.

9. Select N fittest agents from current (λ) and opposite population $(O\lambda)$ as current population (λ).

10. Determine the mass of every agent as (2.4) and gravitational constant as (2.6) respectively.

11. Calculate all agents' acceleration as (2.5).

12. Update the respective velocity and position of the agent as (2.7).

13. If the maximum number of iterations are not exceeded, go to Step 3, otherwise the procedure will be stopped and the optimum bidding strategy printed.

5.5 Result and Discussion

In this section, optimal coordinated bidding strategy between energy and reserve markets is considered for six generating units system. The considered framework is utilized to obtain the maximum profit for power suppliers. The respective supplier's output limits in the spinning reserve market, energy market, and supplier's fuel cost coefficients are given in Table A.8 and taken from [65]. Also, the considered value of D_e and D_{sr} are 1000 MW and 100 MW respectively. The solution obtained by using OGSA is compared with GSA and RGA [65] to demonstrate the capability of OGSA. The tuning parameters of the OGSA are given in Table A.2. The simulations are carried out using MATLAB R2014a software on 3.20 GHz, $i5$ processor, 4GB RAM PC.

For instance, the essential methodology of constructing the strategic bidding for the 6^{th} supplier is explained here. The overall output limit of the 6^{th} supplier is 250 MW, and this is the sum of its output limits in both markets. Estimated output limit of spinning reserve for 6^{th} supplier in scenario first and second is to be really used as $0.1 \times D_{sr}$ and $0.2 \times D_{sr}$ respectively. Subsequently $K_6 = 0.1$ for scenario first and $K_6 = 0.2$ for scenario second has been obtained.

From the perspective of the 6^{th} power supplier in the energy market, every one of the five opponent power supplier is supposed to have an expected joint normal distribution for the two coefficients of bidding, α_m and β_m, $(m = 1, 2, \ldots, 5)$. Similarly, from the perspective of the 6^{th} power supplier in the spinning reserve market, every one of the five opponent power supplier is supposed to have an expected joint normal distribution for the two coefficients of bidding, ψ_m and ξ_m, $(m = 1, 2, \ldots, 5)$.

The approximation of bidding coefficient's in a joint normal distribution for the five opponents in energy and spinning reserve market are given in Table 5.1 and taken from [65] . Therefore in this work, supplier fix the values of $\alpha_6 = a_6$ and $\psi_6 = 0.5 \times b_6$, and employs the OGSA to determine optimal values of β_6 and ξ_6 for developing its strategic bidding. The optimal values of β_6 and ξ_6 are searched in the interval between $[b_6, 20b_6]$ and $[0, 10b_6]$

TABLE 5.1: Estimation of parameters for the five opponents

Estimation of five opponents suppliers in energy market					Estimation of five opponents suppliers in reserve market				
$\mu_m^{(\alpha)}$	$\mu_m^{(\beta)}$	$\sigma_m^{(\alpha)}$	$\sigma_m^{(\beta)}$	ρ_m	$\mu_m^{(\psi)}$	$\mu_m^{(\xi)}$	$\sigma_m^{(\psi)}$	$\sigma_m^{(\xi)}$	γ_m
$1.2 \times a_m$	$1.2 \times 2b_m$	$0.0375 \times a_m$	$0.0375 * b_m$	-0.1	$0.5 \times \mu_m^{(\alpha)}$	$0.5 \times \mu_m^{(\beta)}$	$0.5 \times \sigma_m^{(\alpha)}$	$0.5 \times \sigma_m^{(\beta)}$	-0.1

respectively. The optimal values of β_6 and ξ_6, Market Clearing Prices (MCPs) for both markets (energy market and reserve market), dispatch of power for each power suppliers in both markets and profit of sixth supplier using proposed OGSA, GSA and RGA [65] for $K_6 = 0.1$ and $K_6 = 0.2$ are given in Table 5.2 and Table 5.3 respectively. From Table 5.2,

TABLE 5.2: Optimal bidding result results for suppliers when $K_6 = 0.1$

PSs	RGA [65]		GSA		OGSA	
	$P^{(e)}$ MW	$P^{(sr)}$ MW	$P^{(e)}$ MW	$P^{(sr)}$ MW	$P^{(e)}$ MW	$P^{(sr)}$ MW
1	180.0	03.7	179.7	11.18	179.8	11.99
2	142.9	17.0	140.9	19.78	139.8	20.00
3	105.0	16.9	104.4	17.98	101.1	19.48
4	194.0	17.7	194.4	22.40	195.5	23.69
5	197.9	14.3	197.4	20.30	194.5	19.87
6	180.2	30.4	183.0	08.35	190.0	04.96
β_6	0.03008		0.031427		0.03081	
ϕ_6	0.00952		0.035086		0.062423	
$MCP^{(e)}$	7.420		7.7627		7.8409	
$MCP^{(sr)}$	1.289		1.2930		1.302	
$PS_{6^{th}}$	606.9		658.66		679.23	

it is noted that the MCPs for both markets are increased using OGSA as compared to GSA and RGA [65]. The MCPs in both markets are proportionally related to profit through revenue. Therefore, profit obtained of the sixth supplier using OGSA is higher than that of GSA and RGA [65] by \$20.57 and \$72.33 respectively. From Table 5.3, it is noted that

TABLE 5.3: Optimal bidding result results for suppliers when $K_6 = 0.2$

PSs	RGA [65]		GSA		OGSA	
	P^{e} MW	P^{sr} MW	P^{e} MW	P^{sr} MW	P^{e} MW	P^{sr} MW
1	181.4	04.1	182.9	12.33	188.7	12.02
2	143.9	17.2	138.6	20.00	140.9	19.73
3	105.7	17.1	104.4	18.58	101.5	18.08
4	195.4	18.1	193.3	24.09	193.4	22.53
5	199.4	14.7	196.2	20.93	196.9	22.48
6	174.3	28.9	185.0	04.07	179.0	05.16
β_6	0.03131		0.031269		0.033181	
ϕ_6	0.01017		0.077507		0.05607	
$MCP^{(e)}$	7.458		7.7724		7.9272	
$MCP^{(sr)}$	1.294		1.305		1.307	
$PS_{6^{th}}$	588.1		656.74		676.13	

the MCPs for both markets are increased using OGSA as compared to GSA and RGA [65]. Therefore, profit obtained of the sixth supplier using OGSA is higher than that of GSA and RGA [65] by \$19.39 and \$88.03 respectively. Moreover, in case of $K_6 = 0.2$, the MCPs for both markets are higher than that of case $K_6 = 0.1$. This is because the sixth power supplier has greater approximation of the really used spinning reserve quantity in case $K_6 = 0.2$ as compared to case $K_6 = 0.1$. Instead of increase the MCPs for both markets, the profit of the sixth power supplier is decreased, because it's generation dispatch in both markets are decreased. Results for case $K_6 = 0.1$ and case $K_6 = 0.2$ shows that the proposed OGSA is more promising as compared to GSA and RGA [65].

5.6 Conclusion

In this Chapter, a method to build bidding strategies, with which power suppliers can optimally coordinate their activities in the energy and spinning reserve markets are presented. In these markets, the PS submits single hour linear supply-bid for energy to the PX, and single hour linear supply-bid for reserve to the system operator. A uniform clearing price rule is applied in both markets. Imperfect knowledge of rivals, including unsymmetrical cases, can be modeled in the proposed framework. The proposed method is tested on 6 supplier system considering 1 supplier as main generator and other 5 as its rival generators. The results indicate the increase in profit of the main generator and its MCP in both markets as compared to that obtained in GSA and RGA. The simulation results validate the efficacy of OGSA in providing better optimal solutions compared to other methods reported previously.

Chapter 6

Conclusions and Scope for Further Research

The objective of this Chapter is to accumulate the major contributions and results of the work performed in this thesis and suggest recommendations for future study work in this field.

6.1 Significant Findings

The present work has been designed to propose the different bidding strategies such as single sided bidding strategy of power suppliers participating in single hour trading period, single sided bidding strategy of power suppliers with ramp rate constraints in multi hour trading period, double sided bidding strategy of power suppliers and large buyers in single hour trading period, single sided and double sided bidding strategy with amalgamation of renewable, and coordinated bidding strategy between energy and reserve markets for profit maximization.

In Chapter 2, optimization techniques are suggested for the solutions of bidding strategies. The following are the chapter's key findings:

1. A modified method of optimization, called the Oppositional Gravitational Search Algorithm (OGSA) is implemented. OGSA's opposition operator helps provide search space where GSA is unable to reach. It helps to avoid searching for an optimal local solution to be trapped.

2. Recently, Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) along with OGSA (TOGSA) is also implemented to achieve the most compromise solution for the contradictory multi-objective optimization issue. This technique expands Euclidean geometry to provide a uniform distribution of outcomes for multi-objective optimization issues.

In Chapter 3, the optimal bidding strategies in single side and double side trading mechanisms is investigated using proposed OGSA and TOGSA respectively for maximization of the profit for market participants. Moreover, the performances of the proposed techniques are compared with the previous solutions using different methods available in the literature. Following are the main conclusions of this chapter:

1. It is observed that from the results of the case I, the MCP and overall profit obtained using OGSA are higher than that of GSA, PSO, GA, and MC. It is also observed from the results that the total generation obtained using OGSA method exactly equals the load demand. It shows that the error between the generation and load demand is zero for OGSA method, and thus OGSA method is highly stochastic compared to GSA, PSO, GA, and MC methods.

2. In case II investigates the ramp rate effect on the profit of the power supplier. A standard is established to the estimation of the outcome of the competition between suppliers for commitment. Also, the process for optimizing the profit of an individual power supplier while ensuring its success in competition with rivals are proposed by fine-tuning the ramp rate and bidding coefficients. The results obtained indicate that the participation of generators in a day- ahead electricity market bidding process without considering ramp rate limits will cause economic loss to the generators as this extra cost is beared by generators. Consideration of hourly ramp rates provides practically feasible values of generation dispatch for each unit. The net profit of generators is also increased by incorporation of hourly ramp rate limits because the market clearing price for each hour is changed. The possible advantages cannot be ignored, and that bidding strategy can provide an opportunity for an individual power supplier to enhance their profit by adjusting their bid to the ramp rates and bidding coefficients. Therefore, proposed bidding strategy considering ramp rate constraints is valuable for the market operator to recognize the effect of ramp rate constraints on the market outcomes and for the power supplier to develop bidding strategy in the light of operational results.

3. It is observed that from the results of the case III, the proposed technique TOGSA is successful increasing the trading of power between suppliers and buyers and thus the value of MCP and objective functions has been improved compared to other reported techniques in terms of result quality. Moreover, the total power output of suppliers is exactly equal to addition of the buyer's demand and forecasted load demand.

Chapter 4 exclusively devoted on bidding strategies with the amalgamation of renewable energy sources with minimization of uncertainties and limitations associated with renewable energy. Also, an appropriate mathematical model is being proposed for market clearing price (MCP) calculation in the presence of renewable energy sources. The effect of renewable energy sources is tested on both single and double side bidding mechanisms in a single hour trading period. Following are the major conclusions of this chapter

1. Wind speed and solar irradiation uncertainties are handled respectively by Weibull and Beta distribution of probability, and transformed into wind and solar power. Further, KDM method is used to reduce the samples of wind and solar power. In addition, the renewable energy variability is measured in terms of overestimation and underestimation.

2. MCP is calculated at modified demand, i.e. actual demand minus renewable power. In this work, the operational cost of the renewable power generator is not considered as it is justifiable to deliberate their imbalance cost due to uncertainty associated with renewable generation. This is measured by the two components of imbalance cost (overestimation and underestimation). This reflects on the net profit gained by renewable power supplier by subtracting imbalance cost from their revenue. Here, the penalty coefficient associated with underestimation and reserve coefficient with overestimation taken as 50% of MCP and equal to MCP, respectively.

3. It is observed that from the results, amalgamations of wind and solar power also affects the bid as it reduces the CPS generation and provides less MCP value that would deliver sufficient electricity from accepted sales bids to meet all accepted purchase bids and increase the total traded power. Further, with the involvement of KDM, overestimation of uncertainty is very less as compared to the underestimation in both the solar and wind power generation. This will encourage the solar and wind power suppliers for bidding the extra power into the real-time market if the underestimation is positive.

In Chapter 5 the optimal coordinated bidding strategy between energy and reserve markets in single side trading mechanism has been examined using proposed OGSA for profit maximization of power suppliers. The proposed method is tested on 6 supplier system considering one supplier as main generator and other five as its rival generators. The results indicate the increase in profit of the main generator and its MCP in both markets as compared to that obtained in GSA and RGA.

The optimization techniques GSA and its proposed variants OGSA and TOGSA are employed to achieve this task. The model and method developed in this research provide a systematic way of investigating the supplier and large buyers profit maximization problem and for building a set of overall coordinated bidding strategies in energy and spinning reserve markets. Also, the generalization of this work will allow researchers to apply the procedures presented in the investigation of bidding strategies in electricity markets to different substitutes. These procedures will help participants in the electricity market to effectively apply bidding strategies and maximize their individual revenues by strengthening their competitive position in electricity markets.

6.2 Future Scopes

As a continuation of this research work, it is hereby suggested that

1. To better represent the transaction behaviors in complex electricity markets, the shortcomings of each method should be overcome by continuously pushing for new theoretical developments. Therefore, new modeling methods and algorithms are to be searched and considered in further research.

2. The task of reducing the emission may be performed by including the emission cost in the fuel cost equation. This will result in multi objective optimization.

3. To develop bidding strategy considering some other constraints such as start-up and shutdown costs, minimum up and down time limits, transmission line constraints, and power loss, etc.

4. To develop strategic bidding considering Pay as Bid (PAB) market clearing pricing rule, Battery Energy Storage System (BESS) and Demand Response etc.

Appendix A

Test Distribution Systems

A.1 IEEE Standard 30-bus System Data

Table A.1: IEEE standard 30-bus system data

PSs	a ($\$/MW$)	b ($\$/(MW)^2$)	PG_{min} (MW)	PG_{max} (MW)
1	2.00	0.00375	20	160
2	1.75	0.0175	15	150
3	1.00	0.0625	10	120
4	3.25	0.00834	10	100
5	3.00	0.025	10	130
6	3.00	0.025	10	130

A.2 Tuning Parameters for Different Techniques

Table A.2: Tuning parameters for different techniques

Parameters	GSA and OGSA	PSO	GA
Size of Population	50	50	50
Iterations	1000	1000	1000
Gravitational Constant (G)	100		
Learning Factors (c1 = c2)		2.0	
inertia constant (w)		0.9 to 0.4	
Length of Chromosome			12
Elitism Probability (Pe)			0.15
Crossover Probability (Pc)			0.85
Mutation Probability (Pm)			0.005

A.3 Six Units With Ramp Rates

TABLE A.3: Six units with ramp rates

PSs	a (\$/MW)	b (\$/$(MW)^2$)	PG_{min} (MW)	PG_{max} (MW)	RD (MW)	RU (MW)
1	4.10	0.00028	50	680	80	85
2	4.50	0.00312	30	150	45	60
3	4.10	0.00048	50	360	60	65
4	3.74	0.00324	60	240	45	80
5	3.82	0.00056	60	300	70	80
6	3.78	0.00334	40	160	35	40

A.4 Twenty Four Time Intervals Load Data

TABLE A.4: Twenty four time intervals load data

Time	1	2	3	4	5	6	7	8	9	10	11	12
Load (MW)	1033	1000	1013	1027	1066	1120	1186	1253	1300	1340	1313	1313
Time	13	14	15	16	17	18	19	20	21	22	23	24
Load (MW)	1273	1322	1233	1253	1280	1433	1273	1580	1520	1420	1300	1193

A.5 Six Power Suppliers and Two Large Buyers System Data

TABLE A.5: Six power suppliers and two large buyers system data

PSs	a (\$/MW)	b (\$/$(MW)^2$)	PG_{min} (MW)	PG_{max} (MW)
1	6.0	0.01125	40	160
2	5.25	0.0525	30	130
3	3.0	0.1375	20	90
4	9.75	0.02532	20	120
5	9.0	0.075	20	100
6	9.0	0.075	20	100
LBs	e (\$/MW)	f (\$/$(MW)^2$)	D_{min} (MW)	D_{max} (MW)
1	30	0.04	00	200
2	25	0.03	00	150

A.6 IEEE Standard 57-bus System Data

TABLE A.6: IEEE standard 57-bus system data

PSs	a ($\$/MW$)	b ($\$/(MW)^2$)	PG_{min} (MW)	PG_{max} (MW)
1	1.7365	0.0017	50	576
2	10.0	0.0100	10	100
3	7.1429	0.0071	20	140
4	10.0	0.0100	10	100
5	1.81	0.0018	40	550
6	10.0	0.0100	10	100
7	2.4390	0.0024	30	410

A.7 PV module specifications

TABLE A.7: PV module specifications

Characteristics of Module	Unit
PV^{max} (Peak of Output)	340 Watt
I_{TK}	0.047 $mAmp/^0C$
V_{TK}	0.335 $mVolt/^0C$
FF (Fill Factor)	0.755
T_a (Ambient Temperature)	25^0C
T_{NO} (Nominal Cell Operating Temperature)	46^0C
I_{mpp} (Current at Maximum Power)	8.99 Amp.
V_{mpp} (Voltage at Maximum Power)	37.8 Volt.
V_{oc} (Open Circuit Voltage)	46 Volt.
I_{sc} (Short Circuit Current)	9.78 Amp.

A.8 Six Power Suppliers Data in Energy and Spinning Reserve Market

TABLE A.8: Six power suppliers data in energy and spinning reserve market

PSs	a $\$/(MW)$	b $\$/(MW)^2$	PG^e_{min} (MW)	PG^e_{max} (MW)	$PG^s_{min}r$ (MW)	$PG^s_{max}r$ (MW)
1	2.25	0.0125	00	200	00	50
2	1.75	0.0175	00	180	00	20
3	1.50	0.0250	00	120	00	30
4	1.90	0.0125	00	220	00	30
5	2.00	0.0120	00	250	00	50
6	2.00	0.0120	00		00	

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Publications

Following papers have been published/accepted out of this thesis work.

International Journals

1. Satyendra Singh and Manoj Fozdar, "Optimal bidding strategy with inclusion of wind power supplier in an emerging power market," IET Generation, Transmission & Distribution, Volume 13, Issue 10, May 2019, p. 1914 - 1922, DOI: 10.1049/iet-gtd.2019.0118.
2. Satyendra Singh and Manoj Fozdar, "Bidding strategy for generators considering ramp rates in a day-ahead electricity market," Turkish Journal of Electrical Engineering & Computer Sciences, DOI: 10.3906/elk-1805-73
3. Satyendra Singh and Manoj Fozdar, "Double-sided bidding strategy for power suppliers and large buyers with amalgamation of wind and solar based generation in a modern energy market," IET Generation, Transmission & Distribution, DOI: 10.1049/iet-gtd.2019.0570

International Conferences

1. Satyendra Singh and Manoj Fozdar, "Generation bidding strategy in a pool-based electricity market using oppositional gravitational search algorithm," in 14th IEEE India Council International Conference (INDICON), pp. 1–6, 2017, IIT Roorkee, DOI: 10.1109/INDICON.2017.8487910
2. Satyendra Singh, Manoj Fozdar and Ajeet Kumar Singh, "Coordinating bidding strategy of profit maximization for competitive power suppliers in energy and reserve markets," 2018 8th IEEE India International Conference on Power Electronics (IICPE), pp. 1-6, 2018, MNIT Jaipur, DOI: 10.1109/IICPE.2018.8709459
3. Satyendra Singh, Manoj Fozdar and Ajeet Kumar Singh, "Optimal strategic bidding using Intelligent Gravitational Search Algorithm for profit maximization of power suppliers in an emerging power market," Intelligent Computing Techniques for Smart Energy Systems (ICTSES' 18), Lecture Notes in Electrical Engineering, Springer.
4. Satyendra Singh and Manoj Fozdar, "Double Sided Bidding Strategy in a Day-Ahead Electricity Market," in ICPS 2019: 8th International Conference on Power Systems, 2019, Malaviya National Institute of Technology Jaipur, Jaipur, India, December 20-22, 2019.

Brief bio-data

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