Int. J. Advance. Soft Comput. Appl., Vol. 3, No. 1, March 2011
ISSN 2074-8523; Copyright © ICSRS Publication, 2011
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Optimal Bidding Strategy in an Open Electricity Market using Genetic Algorithm

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Abstract

In this paper optimal bidding strategy problem modeled as a stochastic optimization problem and solved using Genetic Algorithm (GA). In an open electricity market environment, maximizing profit by suppliers is possible through strategic bidding. Because of the gaming by participants (power suppliers and large consumers) in an open electricity market, this is more an oligopoly than a competitive market. Each participant can increase their own profit through strategic bidding but this has a negative effect on maximizing social welfare. It is assumed that each supplier/large consumer bids a linear supply/demand function, and the system is dispatched to maximize social welfare. Each supplier/large consumer chooses the coefficients in the linear supply/demand function to maximize benefits, subject to expectations about how rival participants will bid. A numerical example with six suppliers and two large consumers is used to illustrate the essential features of the proposed method and the results are compared with a Monte Carlo approach. Test results indicate that the proposed algorithm gives more profit, converge much faster and more reliable than Monte Carlo approach.

Keywords: – *Electricity Market, Deregulation, Market Clearing Price (MCP), optimal bidding strategy, Independent System Operator (ISO), Genetic Algorithm (GA).*

1 Introduction

In restructured electricity market, generators must either submit profit-maximizing bids to a pool or optimally self-schedule in response to prices. In some market designs bids are simple bids (offers) to sell a certain amount of energy or some other service the unit is able to provide at a given price or better. This yields to restructuring of currently Vertically Integrated Utility (VIU) to the main three utilities, namely Generation Company (GENCO), Transmission Company (TRANSCO) and Distribution Company (DISCO). The success in the energy privatization in the countries like UK, USA, Norway and Australia has encouraged many more countries to privatize their electricity industry. India has also participated in the process and most of the states of India have restructured their electricity boards. Ever since the restructuring has taken place, the electric power industry has seen tremendous changes in its operation and governance. Electricity, being a concurrent entity, cannot be stored easily, this emphasis on generation and consumption of electricity at the same moment of time. Ascertain of electricity market gave new dimension on power system engineer and the economics of power system.

In developed countries Electricity market is already functioning and it is being started to introduce in developing countries. The sole purpose of introduction of deregulation and electricity market is to create a healthy competition among the participant of the market and to make electricity market more efficient, liquid and complete [1].The fundamental objectives behind the establishment of electricity market are the secure operation of power system and facilitating an economic operation of the system. Key entities of the electricity market are Generating companies (GENCOs), Independent System Operator (ISO) many a times known as System Operator (SO), Transmission Companies (TRANSCOs) and Distribution Companies (DISCOs) [2]. The development of electricity market also aims for the maximum participation from the electric utilities to provide transparent and non-discriminatory platform for energy producers.

In recent years, some research works have been published on optimal bidding strategy based on classical optimization theory as well as evolutionary methods. David and Wen [3-5] have modeled the strategic bidding as a stochastic optimization problem for single period auction. Reinforcement learning was used to find the optimal bidding strategy in [6, 7]. Ferrero and Feng Zhao and Taghi et al. [8, 9 and 10] proposed Game Theory based bidding method. Weber and Zhang [11, 12] proposed optimization based bidding strategies. Richter [13] proposed comprehensive bidding strategies with GA. In this paper, the bidding strategy problem is modeled as an optimization problem and Genetic Algorithm (GA) is presented to solve the bidding strategy problem. The profit’s deviations for all participants are analyzed in detail. Cases studied based on a modified 6-bus system is presented as illustrations [4]. Numerical analysis will clarify importance of strategic bidding on social welfare.

2 Electricity Market Architecture

The electricity market architecture comprises of main four entities namely GENCOs, TRANSOs, DISCOs and an Independent System Operator (ISO). GENCO is not necessary to have its own generating plants, but it can negotiate on behalf of generating companies. In ancillary market GENCO has opportunity to sell its reserves and reactive power. The GENCO will try to maximize its own profit, whatever way it can, by selling the power in the market. TRANSCO transmit the power from power producer to power consumer. It also maintains the transmission system to increase overall reliability of power system. DISCO distributes the power to retail companies, brokers or to its own consumers. ISO is an independent body which maintains the instantaneous power balance in the system. ISO is also responsible for secure operation of the grid. There could be two types of ISO, one is known as MinISO and the other is MaxISO [14]. While MinISO, looking after the grid security and has no role in power market, MaxISO model includes power exchange (PX). The function of power exchange is to provide a competitive market place for all the participant of the market. ISO uses the assets of TRANSCO for its functioning. The role of ISO also encompasses the fare use of transmission network, maximizing social welfare of the market, running Power Exchange (PX), and maintaining grid security and to run separate market for ancillary services.

From the Fig.1 the equilibrium point is known as Market Clearing Price (MCP). The ISO or PX accepts bids from all the players of the market and determines the MCP. Whenever there is no network congestion, MCP is the only one price for every node of the system [15]. But because of the congestion the whole system is being segregated in different zones and zonal market clearing price is used for different zones.

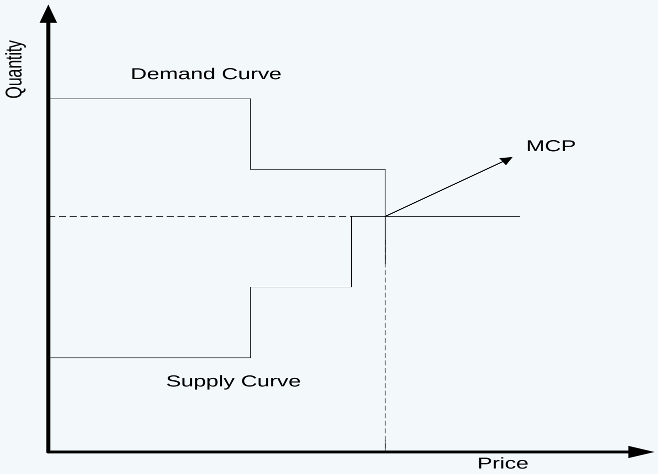

Fig.1. Market Equilibrium Point

3 Model of Bidding Strategy

Suppose that a system consist of ‘*m*’ Independent Power Producers (IPPs), an inter-connected network controlled by an ISO, a power exchange (PX), an aggregated consumer (load) which does not participate in demand-side bidding but is elastic to the price of electricity, and ‘*n*’ large consumers who participate in demand-side bidding. Next assume that each supplier/large consumer is required to bid a linear non-decreasing supply/non-increasing demand function to PX, say bid linear supply curve denoted by $G_i\left(P_i\right)=a_i+b_iP_i$ when *i= 1,2,.....m* and for large consumers bid linear demand curve denoted by $W_j\left(L_j\right)=c_j-d_jL_j$ when *j=1,2,....n.* Here P_i is the active power output, a_i and b_i the bidding coefficients of the i^{th} supplier L_j is the active power load. c_j and d_j the bidding coefficients of the j^{th} large consumer; a_i , b_i , c_j and d_j are non-negative.

Now, the main function of PX is to determine a generation/demand dispatch/schedule that meets security and reliability constraints using transparent dispatch procedures, with the objective of maximizing social welfare. Moreover, when the suppliers/large consumers bid linear supply/demand functions and the network constraints are ignored, maximizing social welfare leads to a uniform market clearing price for all suppliers and consumers [16]. Thus, when only the load flow constraints and generation output limit and consumer demand limit constraints are considered, PX determines a set of generation outputs $P = (P_1,P_2\ldots P_m)^T$ and a set of large consumers’ demands $L = (L_1,L_2,\ldots L_n)^T$ by solving problems (1) to (5). In practice, additional constraints such as transmission capacity constraints need to be included. The procedure of the method presented below can be adapted to the more complex situation, and this will be accounted for in later studies.

$$a_i+b_iP_i=R \quad i=1,\,2\,\ldots m \tag{1}$$

$$c_j-d_jL_j=R \quad j=1,\,2\ldots\ldots n \tag{2}$$

$$\sum_{i=1}^{m}P_i=Q(R)+\sum_{j=1}^{n}L_j \tag{3}$$

$$P_{\min,i}\le P_i\le P_{\max,i} \quad i=1,\,2\ldots\ldots m \tag{4}$$

$$L_{MIN,J}\le L_j\le L_{\max,j} \quad j=1,\,2\ldots\ldots n \tag{5}$$

R is the uniform market clearing price of electricity to be determined. *Q(R)* is the aggregate pool load forecast by PX and made known to all participants and is assumed to be dependent on the price of electricity. $P_{min,i}$ and $P_{max,i}$ are the generation output limits of the i^{th} supplier, and $L_{min,j}$ and $L_{max,j}$ are the demand limits of the j^{th} large consumer. The expression for *Q(R)* is available, Eqs. (1) - (3)

can be solved directly. The procedure is basically the same as that for the classical economic dispatch problem [17]. Suppose the aggregate pool load *Q(R)* takes the following linear form:

$$Q(R)) = Q_o - KR \tag{6}$$

where *Qo* is a constant number and *K* is a coefficient denoting the price elasticity of the aggregate demand. If pool demand is largely inelastic, then *K=0.* The inequality constraints (4) and (5) are ignored, the solution to Eqs. (1) - (3) are:

$$R = \frac{Q_o + \sum_{i=1}^{m} \frac{a_i}{b_i} + \sum_{j=1}^{n} \frac{c_j}{d_j}}{K + \sum_{i=1}^{m} \frac{1}{b_i} + \sum_{j=1}^{n} \frac{1}{d_j}} \tag{7}$$

$$P_i = \frac{R - a_i}{b_i} \qquad i=1, 2\ldots m \tag{8}$$

$$L_j = \frac{c_j - R}{b_j} \qquad j=1, 2 \ldots n \tag{9}$$

When the solution set (8)/(9) violates generation output/consumer demand limits (4)/(5), it must be modified to accommodate these limits. When P_i is smaller than its lower limit $P_{min,i}$, P_i should be set to zero rather than $P_{min,i}$ and the supplier removed from the problem since the supplier ceases to be competitive. When it is larger than the upper limit its value is set to $P_{max,i}$ and Eq. (1) ignored for this generator since it is no longer a marginal generator. In these two cases, Eq. (1) no longer holds for supplier i. similar treatment is applicable to L_j. For the i^{th} supplier has the cost function denoted by $C_i(P_i) = e_i P_i + f_i P_i^2$, the benefit maximization objective for building a bidding strategy can be described as:

$$\text{Maximize: } F(a_{i,} b_i) = RP_i - C_i(P_i) \tag{10}$$

Subject to: Eqs. (1) - (5)

This is to determine a_i and b_i so as to maximize $F(a_i, b_i)$ subject to the constraints (1) - (5). $C_i(P_i)$ is the production cost function of the i^{th} supplier. Similarly, for the j^{th} large consumer has revenue function $B_j(L_j) = g_j L_j - h_j L_j^2$, the benefit maximization objective for building a bidding strategy can be described as:

$$\text{Maximize: } B(c_j, d_j) = B_j(L_j) - RL_j \tag{11}$$

Subject to: Eqs. (1)-(5)

This is to determine c_j and d_j so as to maximize $B(c_j, d_j)$ subject to the constraints (1) - (5). $B_j(L_j)$ is the demand (benefit) function of the j^{th} large consumer. In the sealed bid auction based electricity market, data for the next bidding period is confidential, and hence suppliers/large consumers do not have the information needed to solve the optimization problem (10)/(11). However, the past bidding histories are available, and estimation of the bidding coefficients of rivals is possible. An immediate problem for each participant is how to estimate the bidding coefficients of rivals.

Suppose that, from the i^{th} supplier's point of view, rival's (j) bidding coefficients obey a joint normal distribution with the following probability density function (pdf):

$$pdf_i(a_j, b_j) = \frac{1}{2\Pi\sigma_j^{(a)}\sigma_j^{(b)}\sqrt{1-\rho_j^2}} \times \exp\left\{-\frac{1}{2(1-\rho_j^2)}\left[\left(\frac{a_j-\mu_j^{(a)}}{\sigma_j^{(a)}}\right)^2 - \frac{2\rho_j(a_j-\mu_j^{(a)})(b_j-\mu_j^{(b)})}{\sigma_j^{(a)}\sigma_j^{(b)}} + \left(\frac{b_j-\mu_j^{(b)}}{\sigma_j^{(b)}}\right)^2\right]\right\} \tag{12}$$

where 'ρ_j' is the correlation coefficient between a_j and b_j, and $\mu_j^{(a)}, \mu_j^{(b)}$ $\sigma_j^{(a)}$ and $\sigma_j^{(b)}$ are the parameter of the joint distribution. The marginal distributions of a_j and b_j are both normal with mean values $\mu_j^{(a)}$ and $\mu_j^{(b)}$, and standard deviations $\sigma_j^{(a)}$ and $\sigma_j^{(b)}$ respectively. Similarly, the above probability density function (pdf) is also used for finding bidding coefficients of the large consumers. Based on historical bidding data these distributions can be determined [18]. Using probability density function (12) for supplier as well as large consumers the joint distribution between a_j and b_j, and between c_j and d_j, the optimal bidding problem with objective functions given in Eqs. (10) and (11) and constraints (1) - (5) becomes a stochastic optimization problem. The optimal bidding problem with objective functions (10)/(11) and constraints (1) - (5) becomes a stochastic optimization problem.

In this paper, GA is used to solve the optimal bidding strategy problem. Results are compared with solutions obtained using Monte Carlo approach. In this work, a_i and c_j are fixed and the values of b_i and d_j are searched through Genetic Algorithm (GA) method, which is very efficient to solve the above stochastic optimization problem, presented in the following section.

4 Solution Algorithm

A Genetic Algorithm (GA) is used to search approximate solutions of combinatorial optimization problems. GA begins with a set of solutions called population. Each solution is represented by a set of bit string (chromosome).

Solutions from one population are taken and used to form a new population. Solutions which are then selected to form new solutions (offspring) are selected according to their fitness. Higher the fitness value, higher chances to reproduce. In general, process of optimal bidding using GA can be summarized as

Step1. Read data, namely cost coefficients of generators e_i, f_i (i=1,2,….m) and consumers cost coefficients g_j, h_j (j=1,2,….n), convergence tolerance, error, step size and max allowed iterations, length of string, L, population size, p_c probability of cross over, p_m probability of mutations, lambda min, lambda max.

Step2. Randomly generate initial population of chromosomes

Step3. Set the iteration count=1

Step4. Set chromosome count=1

Step5. Decode the chromosome and calculate the actual value of b_i, d_j.

Step6. Calculate the fitness value using equation (10) and (11).

Step7. Increment chromosome count by 1 and repeat the procedure from Step 4 until chromosome count=population size.

Step8. Sort the chromosomes and all their related data in the descending order of fitness.

Step9. Calculate error from equation (12)

Check if the error is less than convergence tolerance. If yes, go to 17.

Step10. Check if fit(1) = fit(last). If yes go to 16.

Step11. Copy P_e chromosomes of old population to new population starting from the best ones from the top.

Step12. Perform crossover on selected parents and generate new child chromosomes, repeat it to get required number of chromosomes.

Step13. Perform mutation on all chromosomes.

Step14. Add all generated child chromosomes to new population.

Step15. Increment iteration count. If iteration count< max. Iteration, go for next iteration, else print “problem not converged in maximum number of iterations”.

Step16. All chromosomes had equal value. Run the program once again by changing GA parameters.

Step17. Problem converged. Print the values of b_i, d_j at which suppliers and consumers get maximum benefit.

In this paper, Genetic Algorithm is applied by using Genetic Algorithm Toolbox which is one of MATLAB toolboxes developed by Math Works, Inc [19]. The proposed algorithm for optimal bidding strategy is shown in fig.1.The GA parameters used are population size 20, elite count 2, cross over 0.8, generations 100, stall generation limit 50, and stall time limit 120 sec.

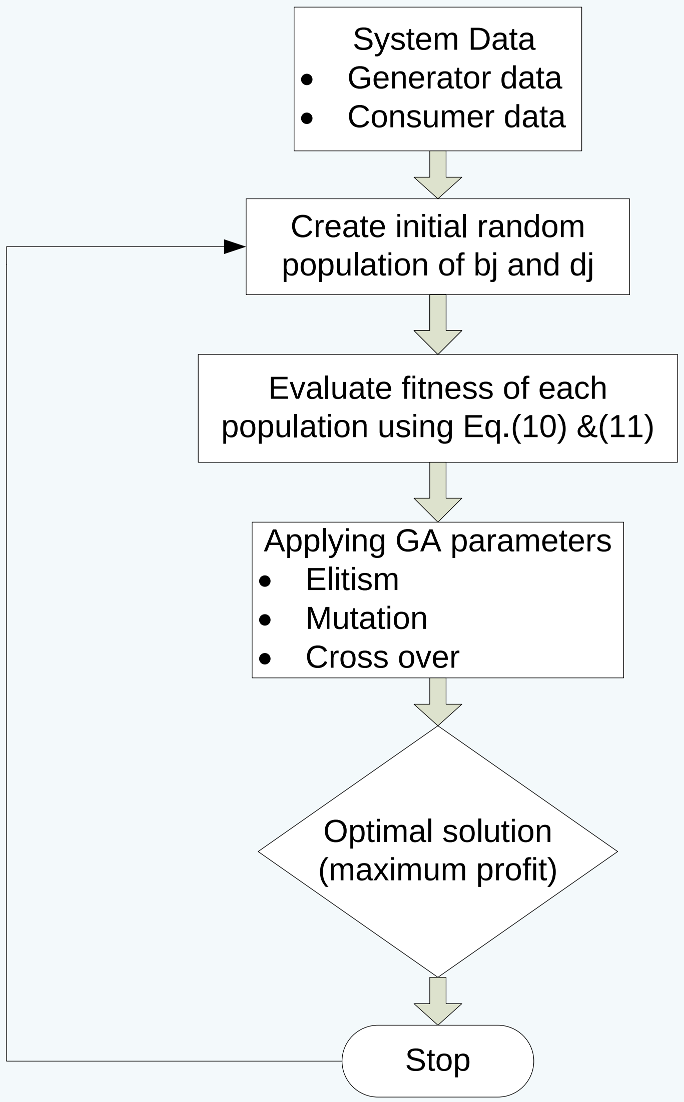

Fig.2. Flow chart of proposed method

5 Results and Discussions

Consider a system consists of six suppliers, who supply electricity aggregate load and two large consumers. Different case studies are analyzed here, which are shown in following tables. The Generator and large consumer data are shown in Table 1. Q_o is 300 and K is 5 for aggregated load.

Table 1: Generator and Large Consumer Data

Generator	e	f	P_{min}(MW)	P_{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
Consumer	g	h	L_{min}(MW)	L_{max}(MW)
1	30	0.04	0	200
2	25	0.03	0	150

5.1 Case A: with symmetrical information

Each rival participant is assumed to have an estimated joint normal distribution for the two bidding coefficients. For the pth participant (p= 1, 2,…, 8), the estimated parameters in the joint normal distributions for the ith supplier (i= 1, 2,…, 6 and i ≠p) and for the jth large consumer (j= 1, 2 and j+ 6 ≠ p), as described in Eq. (12) are specified in Genetic Algorithm as Eqs. (13) and (14):

$$\mu_i^{(a)} = 1.2e_i \quad \mu_i^{(b)} = 1.2 \times 2 f_i$$

$$4\sigma_i^{(a)} = 0.15e_i \;\; 4\sigma_i^{(b)} = 0.15 f_i \tag{13}$$

$$\rho_i = -0.1$$

$$\mu_j^{(c)} = 1.2g_j \quad \mu_j^{(d)} = 1.2 \times 2h_j$$

$$4\sigma_j^{(c)} = 0.15e_j \;\; 4\sigma_j^{(b)} = 0.15 f_j \tag{14}$$

$$\gamma_j = 0.1$$

It should be mentioned that the parameters in Eq. (13) and (14) should be estimated using available mathematical methods such as the one in Ref. [20] based on sufficient historical bidding data. Since we do not have such data, we are unable to determine these parameters mathematically, and instead, these parameters are specified here to illustrate the basic feature of the method and these specifications may not well reflect practical situations. Some explanation about the specifications of parameters in Eq. (13) and (14) is necessary. It is a reasonable assumption that a supplier who is aware of market power in the reformed electricity market is likely to bid above the production cost. Hence, the expected values of a_i and b_i, i.e. $\mu_i^{(a)}$ and $\mu_i^{(b)}$ are specified 20% above e_i and $2f_i$, respectively. The standard deviations of a_i and b_j, i.e. $\sigma_i^{(a)}$, $\sigma_i^{(b)}$ are specified to make a_i and b_i fall in the domains $[1.05e_i, 1.35e_i]$ = [$\mu_i^{(a)}$ $4\sigma_i^{(a)}$ $\mu_i^{(a)}$ $4\sigma_i^{(a)}$] and $[1.05\times2f_i, 1.35\times2f_i]$ = [$\mu_i^{(b)}$ $4\sigma_i^{(b)}$ $\mu_i^{(b)}$ $4\sigma_i^{(b)}$] respectively, with probability 0.9999. ρ_i is specified to be negative because when a supplier decides to increase one of his or her bidding coefficients, it is more likely that, in a mature market, it will decrease rather than increase the other coefficient.

A similar explanation is applicable to the specifications of parameters in Eq. (14), by using Genetic Algorithm (GA) bidding coefficients, generation outputs, market clearing price and profits of six suppliers and two large consumers are calculated and compared with Monte Carlo method, given in Table 2. It is found that GA gives lesser values of the bidding coefficients than Monte Carlo, thereby increasing the dispatched power, market clearing price, expected profit and the actual profit. Fig 3 shows the expected profit of each supplier and large consumer, and the social welfare using GA is $1289 where as using Monte Carlo it is $1286. Therefore using GA the overall profit is increased.

Table 2: Comparative Results of Bidding Strategies and Associated Variables

	Monte Carlo				GA			
Generator	Parameter (b_i)	Dispatch	Profit	MCP	Parameter (b_i)	Dispatch	Profit	MCP
1	0.0292	160.00	1368.0		0.064	160.00	1370.1	
2	0.1242	89.40	572.7		0.105	105.83	588.1	
3	0.2923	45.70	322.9	16.350	0.275	48.592	324.7	16.363
4	0.0743	88.80	386.4		0.055	120.00	428.9	
5	0.1705	43.10	177.5		0.150	49.085	180.7	
6	0.1705	43.10	177.5		0.150	49.085	180.7	
Consumer	d_j	Demand			d_j	Demand		
7	0.0977	139.7	1126.3		0.080	170.463	1162.3	
8	0.0771	112.1	592.6		0.060	143.951	621.7	

Fig 4 shows the expected dispatched powers of the suppliers, it can be clearly seen that power output of suppliers using GA are more than Monte Carlo approach. The time taken by proposed method for 200 generations is 4.30 sec, which is less than the Monte Carlo method.

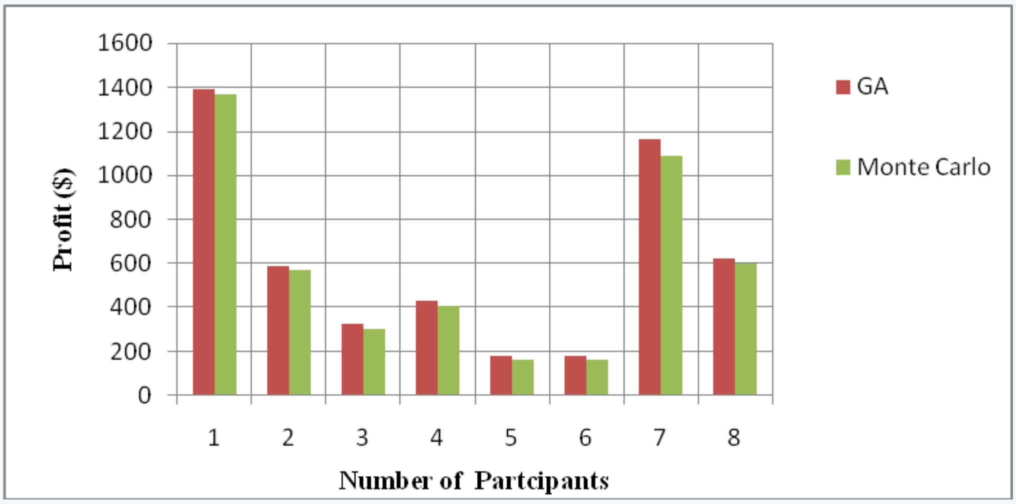

Fig.3 Expected profit of suppliers and consumers

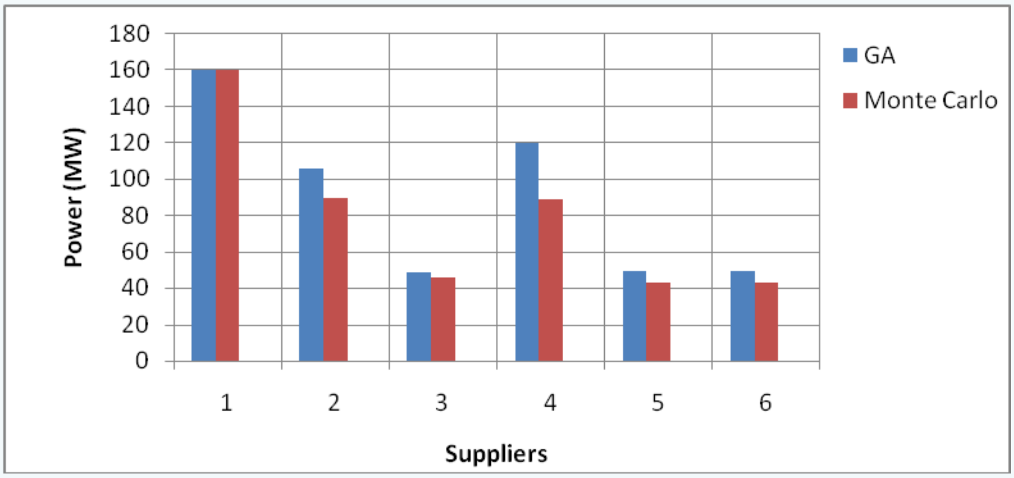

Fig.4 Expected dispatch powers of suppliers

5.2 Case B: with unsymmetrical information

In this case some participants to make better estimates than others could be included in the model. We now describe simulation results for an unsymmetrical situation in which the second supplier has less accurate estimates than the others. The second supplier's estimated expectation values of a_i and b_i, i.e. and for i= 1, 3, 4, 5, 6, are specified to be $1.4e_i$ and $1.4 \times 2f_i$, respectively, while the estimates of the other five suppliers and two consumers are the same as Eqs.(13) and (14), respectively, and all other relevant parameters are the same as in Case A. by using this information, biding parameters, market clearing price, expected profit and expected dispatch of generators and demand of consumers are calculated using proposed method and compared with Monte Carlo method, shown in Table 3. by comparing the results of Case A and case B, in Case B the second supplier moves up the market clearing price by making higher estimates about the bids of rival suppliers and hence offering a higher bid. These optimal strategies lead to an overall increase in benefits for all suppliers, but supplier 2, who has worse information than the others, suffers a benefit reduction.

Fig.5 shows the values of dispatched powers of generators and demand of consumers obtained by using proposed method for Case A and Case B, and it is observed that the overall increase in benefit of all the suppliers except supplier 2, who has worse information than the others, suffers benefit reduction.

Table 3: Comparative Results of Bidding Strategies and Associated Variables

	Monte Carlo				GA			
Generator	Parameter (b_i)	Dispatch	Profit	MCP	Parameter (b_i)	Dispatch	Profit	MCP
1	0.0292	160.00	1411.3		0.073	160.0	1590.6	
2	0.1536	74.00	553.9		0.294	35.34	183.6	
3	0.2923	46.60	336.1	16.62	0.275	53.60	395.1	17.74
4	0.0743	92.40	418.8		0.066	120.0	594.4	
5	0.1705	44.70	190.8		0.150	58.27	254.7	
6	0.1705	44.70	190.8		0.150	58.27	254.7	
Consumer	d_j	Demand			d_j	Demand		
7	0.0977	136.9	1082.0		0.080	153.23	939.2	
8	0.0771	108.6	556.1		0.060	120.97	439.1	

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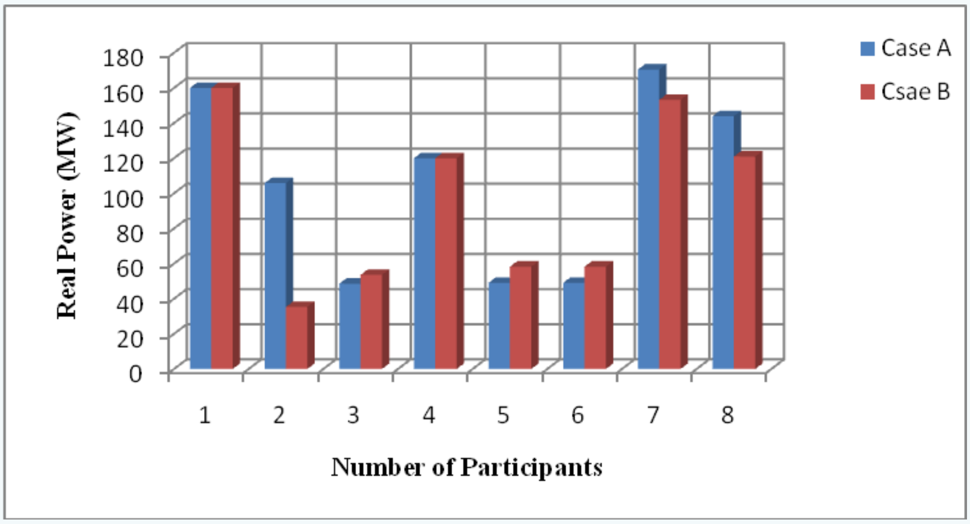

Fig.5.Optimal dispatch of Generators and demnd of Consumers

6 Conclusion

In this paper, application of GA for bidding strategy approach is proposed for suppliers and large consumers in an open electricity market. In this approach, each participant tries to maximize their profit with the help of information announced by system operator. Symmetrical and Unsymmetrical information of rivals are discussed and it is observed that, those who are having imperfect information will suffer profit reduction. This proposed algorithm results in the same solution as Monte Carlo simulation with more profit, much less computing effort and fast convergence. The proposed algorithm can be easily used to determine the optimal bidding strategy in different market rule, different fixed load, different capacity of buyers and sellers. For future research, this work can be extended for 24 hours for competitive day-ahead auction problem considering minimum up and down times.

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