Optimal Bidding Strategy for GENCO in Deregulated Electricity Market by Using Particle Swarm Optimization (PSO)

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Abstract – *Bidding strategies are highly associated with profit maximization. In deregulated electricity market GENCOs (suppliers) and large consumers (buyers) need a optimal bidding model to maximize their profits. Therefore each GENCO and large consumer bids strategically for selection of bidding coefficient to check out rivals bidding strategy. In this paper bidding strategy problem is modeled as an optimization problem and solved by using particle swarm optimization (PSO) method. PSO has many similarities with evolutionary computational techniques such as Genetic Algorithm (GA). However unlike GA, PSO has no evolution operators such as mutation and crossover. The proposed method is tested with IEEE-30 bus system in which 6 generators and 2 loads are considered. Results are compared with the solution obtained using Monte Carlo method. Test results indicate that the proposed algorithm gives more profit, and more reliable than Monte Carlo approach.*

Key Words: Deregulated Electricity Market, Bidding Strategy, Market Clearing Price (MCP), Particle Swarm Optimization (PSO).

1. INTRODUCTION

The Indian power market has change significantly over the past few years. This is mainly due to three factors, emergence of competitive bidding, growth of bilateral trading and introduction of power exchange. Restructuring of the power industry mainly aims to abolishing the monopoly in the generation and trading sectors. There by, introducing competition at various levels wherever it is possible. But the sudden changes in the electricity markets have a variety of new issues such as oligopolistic nature of the market, supplier's strategic bidding, market power misuse, price demand elasticity and so on.

Before deregulation a traditional monopoly structure was exist in the power sector market. But After deregulation process the Large consumers (buyers) and generators (suppliers) starts to interact regarding power transaction and maintain system security through Independent system operator (ISO). Competitive electricity market consist of several Generating Companies, Transmission Companies and Distribution Companies along with the ISO. However, the emergent electricity market structure is more akin to oligopoly than perfect market competition. This is due to special features of the electricity supply industry such as, a limited number of producers, larger investment size (barrier to entry), transmission constraints which isolate consumers from effective reach of many generators, and transmission losses which discourage consumers from purchasing power from distant suppliers. All these make it practicable for only a few generating companies to service a given geographic region and in this setting each supplier can maximize profit through strategic bidding.

Theoretically, in a perfectly competitive market, supplier should bid at their marginal production cost to maximize their profit. However, practically the electricity markets are oligopolistic nature, and power suppliers may seek to increase their profit by bidding a price higher than marginal production cost. Knowing their own costs, technical constraints and their expectation of rival and market behavior, suppliers face the problem of constructing the best optimal bid. This is known as a **strategic bidding problem [15]**.

In day ahead electricity market Price forecasting provide crucial information for power producers and consumers to develop bidding strategies in order to maximize profit.

In recent years, considerable amount of work has been published on strategic bidding for GENCOs and large consumers in deregulated electricity market.

A complete review of optimal bidding strategies in Electricity Market (EM) has been published in [1]. In [2] David proposed Dynamic Programming (DP) based approach to solve strategic bidding problem. A Lagrangian relaxation-based approach for strategic bidding in England-Wales pool type electricity market has been adopted in [3]. The same approach for daily bidding and self-scheduling decision in New England market has been suggested by Zhang et al. in [4]. A considerable amount of work has also been reported on the game theory applications in the competitive electricity markets. In non-cooperative game theory approach [5, 6], strategic bidding problem was solved using Nash equilibrium. Genetic Algorithm (GA) has been proposed by David and Wen in

[7] to develop an overall bidding strategy using two different bidding schemes for a day-ahead market. The same methodology has been extended for spinning reserve market coordinated with energy market in [8]. Ugedo et al. in [9] have proposed a stochastic-optimization approach for submitting the block bids in sequential energy and ancillary services markets, and uncertainty in demand and rival's bidding behavior is estimated by stochastic residual demand curves based on decision trees. In [10], A stochastic programming model has been used to construct linear bid curves in the Nord-pool market for price-taking retailer whose customers load is price flexible. Opponents bidding behaviors are represented as a discrete probability distribution function in [11] and as a continuous probability distribution function in [12] for a supplier's bid decision-making problem. In [13], affect of selection of mutation parameter in GA for bidding strategies is explained. In [14] considering risk constraint, the bidding for single sided and double sided was modeled and solved using GA. Recently bi-level programming and swarm algorithm have been applied to model the competitive strategic bidding decision making in the electricity markets [17].

In general, strategic bidding is an optimization problem that can be solved by various conventional and non-conventional (heuristic) methods. Depending on the bidding models, objective functions and constraints may not be differentiable and then conventional method can't be applied. Heuristic methods such as GA, Simulated Annealing (SA), Evolutionary Programming (EP), and PSO have main limitations of their sensitivity to the choice of parameters, such as the crossover and mutation probabilities in GA, temperature in SA, scaling factor in EP, etc. PSO is a modern stochastic search algorithm and a kind of evolutionary computational technique [16, 19].

In this paper, the bidding strategy problem is modeled as an optimization problem and Particle Swarm optimization is presented to solve the bidding strategy problem. The profit deviations of all participants are analyzed in detail and compared with Mote Carlo method.

1.1 Bidding Scenario in India

Power exchanges in India was commence in 2008. There was a need for a market place in India, where large consumer (buyers) and generators (sellers) could meet and buy or sell power with genuine price discovery. The motivation for establishing such market place in India comes from the Electricity Act 2003, which is the first act to introduced the concept of non-discriminatory open access of power through rules and regulation for promoting competition in the electricity market. As the major step taken by the Electricity Act 2003, the country's power markets have been witnessing significant innovation. Further efforts are positive regulatory that create a competitive market and supported by the efforts of market operators to introduce new products and solutions that benefit consumers, suppliers and the power sector as a whole. Before the functioning of power exchanges in India, an alternatives method was used for purchasing short-term power that consist the unscheduled interchange (UI) market (where prices were volatile) and over the-counter (OTC) trading mechanisms (which typically have high transaction costs). Only the OTC mechanisms continue to serve an important function, earlier consumers wanted a platform that allowed them to enter standardized contracts, take care of counterparty risks, and provided fixed acceptable future electricity price signals. The customer demand for such contracts led to the evolution of power exchanges in India. At present, the power exchanges of India account for 30 percent of the power transacted in the short-term market, so serving as a valuable link in bridging the power demand supply gap.

The **Indian Energy Exchange (IEX)** is the leading energy trading platform of India. Earlier it started operations with a few of participants. But at present, the number of participants registered on the exchange has increased to 6238 comprising 29 states, 5 union territories (UTs). Over 4,500 registered participants were eligible to trade electricity contracts and over 4,100 registered participants were eligible to trade RECs, as of March 2018. Out of participants registered to trade electricity contracts include 54 distribution companies, over 450 electricity generators and over 3,900 open access consumers [18].

The IEX provides a platform for trading power in two type of market first is the day-ahead market (DAM) and second is the term-ahead market (TAM). IEX also started Renewable Energy Certificate (REC).

2. PROBLEM FORMULATION

Consider a system consist of '*m*' Generators, 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. The supplier and large consumer is required to bid a linear non-decreasing supply and non-increasing demand function to PX, bid linear supply curve denoted by $G_i(P_i) = a_i + b_i P_i$ when $i=1,2,.....m$ and for large consumers bid linear demand curve denoted by $W_j(L_j) = c_j - d_j L_j$ when $j=1,2,....n$. Here P_i is the active power output, a_i and b_i *are* the non-negative bidding coefficients of the i^{th} suppliers. L_j is the active power load, c_j and d_j *are* the non-negative bidding coefficients of the j^{th} large consumer.

The main function of PX is to determine a generation/demand schedule that meets security and reliability constraints using transparent dispatch procedures, with the objective of maximizing **social welfare**. Here the Sum of *Consumer's surplus* and *Supplier's surplus* is called ***Social Welfare*** (Fig. 1).

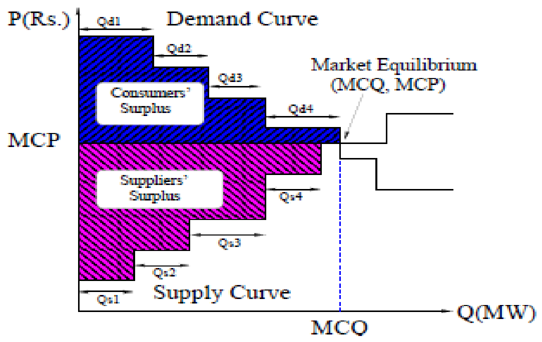

Fig. 1: Market equilibrium and Social Welfare

when only the load flow constraints and generation output limit and consumer demand limit constraints are considered, PX determines a set of generation outputs $P = (P_1,P_2...P_m)^T$ and a set of large consumers' demands $L = (L_1,L_2,....L_n)^T$ by solving equations (1) to (5).

$$a_i + b_iP_i = R \quad i = 1,2,3.....m \text{ ---------------------------- } (1)$$

$$c_j + d_jL_j = R \quad j = 1,2,3.....n \text{ ---------------------------- } (2)$$

$$\sum_{i=1}^{m} Pi = Q(R) + \sum_{j=1}^{n} Lj \text{ ---------------------- } (3)$$

$$P_{min,i} \le P_i \le P_{max,i} \quad i=1,2...m \text{ --------------- } (4)$$

$$L_{min,j} \le L_j \le L_{max,j} \quad j=1,2....n \text{ ----------------- } (5)$$

Where R is Market clearing price (MCP). 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. Suppose the aggregate pool load $Q(R)$ takes the following linear form:

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

where Q_o is a constant number and K is a price elasticity coefficient of the aggregate demand. If pool demand is largely inelastic, then $K=0$. The inequality constraints (4) and (5) are ignored, the solutions to equations (1) to (3) are:

$$R = \frac{Qo + \sum_{j=1}^{n}\frac{cj}{dj} + \sum_{i=1}^{m}\frac{ai}{bi}}{K + \sum_{i=1}^{m}\frac{1}{bi} + \sum_{j=1}^{n}\frac{1}{dj}} \text{ ---------- } (7)$$

$$Pi = \frac{R-ai}{bi} \quad i = 1,2 \ldots..m \text{ -------- } (8)$$

$$Lj = \frac{cj - R}{dj} \quad j = 1,2 \ldots...n \text{ ---- } (9)$$

When the solution set (8) and (9) violates generation output/consumer demand limits (4) and (5), then it must be modified to accommodate these limits. For the i^{th} supplier has the cost function denoted by :

$C_i(P_i) = e_i P_i + f_i P_i^2$

Here e_i and f_i are cost function coefficients.

The Profit maximization objective for bidding strategy can be described as:

Maximize Profit : $F(a_i,b_i) = RP_i - C_i(P_i)$ -----------------(10)

Subjected to : eqs. (1) – (5)

Here RP_i gives total Revenue of i^{th} generators.

To maximize Profit $F(a_i,b_i)$ we have to determine optimum value of bidding coefficient a_i and b_i.

Similarly, for the j^{th} large consumer has revenue function $B_j(L_j) = g_jL_j - h_jL_j^2$, here g_j and h_j are the demand function coefficients. Then profit maximization objective for building a bidding strategy can be described as:

Maximize Profit : $G(c_j,d_j) = B_j(L_j) - RL_j$ --------------- (11)

Subjected to : eqs (1) – (5)

To maximize Profit $G(c_j,d_j)$ we have to determine optimum value of bidding coefficient c_j and d_j **.** In the sealed bid auction electricity market data for next bidding period is confidential, hence suppliers/large consumers don't have the information needed to solve the optimization problem. But past bidding histories are available, then to estimate the bidding coefficients of rivals we will use probability density function. Suppose, from i_{th} supplier's point of view, rival's(j)bidding coefficient obey a joint normal distribution with fallowing (PDF) function as:

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

Where ρ_j = correlation coefficient between a_j and b_j.

μ_j and σ_j are the parameters of joint distribution.

Similarly, Same probability density function (PDF) can be written for large consumers also. Which will be used for finding the bidding coefficients of large consumers. Now with probability density function (PDF) and equation (10) & (11) subjected to condition given in equation (1) to (5) becomes a stochastic optimization problem. That is to solve with the help of optimization technique. In this paper PSO is used to solve the bidding strategy problem.

3. PARTICLE SWARM OPTIMIZATION (PSO)

Particle swarm optimization is one of the most popular nature-inspired meta-heuristic optimization Algorithm developed by a social psychologist James Kennedy and an Electrical Engineer Russell Eberhart in 1995. The PSO technique is an optimization technique that is based on social interaction such as bird flocking and fish schooling. This technique is suitable for any non-linear or random optimization problem. Recently, PSO has emerged as a promising algorithm in solving various optimization problems in the field of Science and Engineering. PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions called particles (Chromosomes in case of GA), fly through the problem space by following the current optimum particles.

Compared to GA, the advantages of PSO are that PSO is easy to implement and there are few parameters to adjust. PSO has been successfully applied in many areas such as: function optimization, artificial neural network training, fuzzy system control, and other areas where GA can be applied.

The basic concept of PSO is that, the optimized result obtained is called as particles and the particles try to fly through the problem space in N dimension by tracking the best optimal result so far of the particles. In PSO initialization is done as, first a mass of random solution is taken and then search for optimal solution by updating the particle weight. In PSO each particle is considered just as a point in a N-dimensional problem space. Equation (13) written below is used for updating the velocity, at each iteration a modified velocity is obtained for each particle based on its previous velocity (Vr k), the particle's location at which the best fitness has been calculated (P_{best} r) so far, and the best particle among the neighbors (G_{best} r) at which the best fitness has been calculated so far. The learning factors C1 and C2 are the acceleration constants that change the velocity of a particle towards (P_{best} k) and (G_{best} k), and rand1, rand2 are uniformly distributed random numbers in [0, 1]. Each particle's position is updated using equation (14) in the solution space. The weight is updated by using equation (15).

$$V_r^{k+1} = W^k.V_r^k + c1.rand1.(P^k_{best} - X_r^k) + C2.rand2.(G^k_{best} - X_r^k) \quad (13)$$

$$X_r^{k+1} = X_r^k + V_r^{k+1} \quad (14)$$

$$W^k = W_{max} - \frac{Wmax - Wmin}{Kmax} * K \quad (15)$$

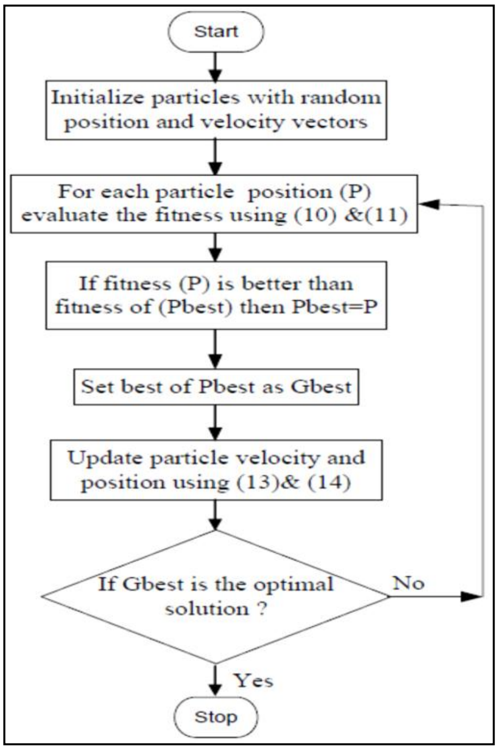

Fig. 2: Flow chart of PSO

3.1 PSO Algorithm for Bidding Strategy

It is obvious that for maximizing the profits of GENCOs and Large consumers both pair of bidding coefficients (a_i, b_i)

and (c_j , d_j) cannot be selected independently. So a_i and c_j are maintained constant and then b_i and d_j are optimized. In this paper PSO is used to find the optimum value of bidding coefficients b_i and d_j and its corresponding value of profits are calculated.

A. PSO for obtaining bidding coefficients (b_i/d_j)

Step 1. Generate random population for b_i and read input data.

Step 2. Calculate fitness evaluation function for individual b_i by using equation (12).

Step 3. Each P_{best} values is compared with other P_{best} and update G_{best}.

Step 4. The member velocity *V* of each individual b_i is modified according to the velocity update (13).

Step5. The position of each individual b_i is modified according to the position update (14).

Step6. Repeat from steps 2-5 until iteration reaches their maximum limit. Return the best fitness (optimal bid value b_i) computed at final iteration as a global fitness. Using b_i values, calculate MCP from (7).

A similar procedure is applied to find the optimal values of d_j.

B. Profit Maximization by PSO

Step 1. Generate random population of profit F_j (a_i, b_i) and read input data of Generators (i.e. cost coefficients, P_{min}, P_{max}), demand (Q_o) and maximum number of iterations.

Step 2. Calculate each generator output using (8).

(a) If generation violates lower limit set as a lower limit.

(b)If generation violates upper limit set as an upper limit.

Step 3. Fitness evaluation by using (10) and (11).

Step 4. Each P_{best} values are compared with the other P_{best} values in the population. The best evaluation value among the P_{bests} is denoted as G_{best}.

Step 5. The member velocity *V* of each individual b_i is modified according to the velocity update (13).

Step 6. The position of each individual b_i is modified according to the position update (14).

Step 7. Repeat from steps 3- 6 until iteration reaches their maximum limit. Return the best fitness (maximum profit) computed at final iteration as a global fitness.

4. RESULT ANALYSIS

Considering a IEEE-30 bus system which consist 6 generators and 2 loads. The data for generators and loads are given in table 1. Q_o = 300, K = 5 for aggregate loads. For PSO, Population size = 50, Acceleration factor: C1 = C2 = 2.0, Inertia weight: W_{max} = 1.0 and W_{min} 0.5, Maximum iteration: K= 150. Simulation is tested on 2.40 GHz, 3GB RAM, Intel core(TM) i3 processor, and MATLAB 2014a version is used.

Table 1. Generators and Large Consumers data

Generator	e_i	f_i	P_{min} (MW)	P_{max} (MW)
1	6.0	0.01125	40	160
2	5.25	0.0525	30	130
3	3.0	0.01375	20	90
4	9.75	0.02532	20	120
5	9.0	0.075	20	100
6	9.0	0.075	20	100
Load	g_j	h_j	L_{min} (MW)	L_{max} (MW)
1	30	0.04	0	200
2	25	0.03	0	150

There are two cases in bidding strategy. In first case all the participant have same information about the past bidding history. But in second case some participants make better estimates than other. In this paper first case is considered.

In electricity market each rival participant is assumed to have an estimated joint normal distribution for the two bidding coefficients. Let us assume the joint normal distribution parameters that are described in PDF equation (12) are defined as.

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

$4\times\sigma_i^{(a)}=0.15\times e_i$ $4\times\sigma_i^{(b)}=0.15\times f_i$ $\rho_i=-0.1$ -----(16)

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

$4\times\sigma_j^{(c)}=0.15\times e_j$ $4\times\sigma_j^{(d)}=0.15\times f_j$ $\gamma_j=0.1$ ----- (17)

A reasonable explanation is not available for the equation (16) and (17). It must be solved with the help of mathematical assumption. But these equations show a distinct pattern which is available in past bidding history. So we can say these equations are the estimation of past bidding data available for all participants. These parameters are just to show the basic features of the method and these equations may not fully reflect the practical situations. Suppliers who know the condition of power market from past history, so want to increase its profit by bid above the production cost (marginal cost). Hence, the expected values of a_i and b_i (i.e, mean value $\mu_j^{(a)},\mu_j^{(b)}$) are specified 20% higher than e_i and $2\times f_i$ respectively. The standard deviations of a_i and b_i (i.e, $\sigma_j^{(a)}$, $\sigma_j^{(b)}$) are specified to make a_i and b_i fall in the range of $[1.05\times e_i, 1.35\times e_i]$ with probability of 0.9999. ρ_i is specified to be negative because it show inverse relation with bidding coefficient means when a generators (supplier) increase one of his bidding coefficients, it is more likely that, in a power market, it will decrease rather than increase the other coefficient.

A similar explanation is applicable for the parameters in equation (17). In this paper by using PSO, bidding coefficients of generators (suppliers) and large consumers (buyers), generators outputs, market clearing price (MCP) and profit of six generators (suppliers) and two large consumers (buyers) are calculated and compared with Monte Carlo method [12], as shown in Table 2 and Table 3. Table 2 shows the optimal bidding coefficient of generators and large consumers, and Table 3 shows the MCP and profit of each generators (supplier) and large consumers.

Table 2. Bidding coefficients of generators and large consumers.

	Monte Carlo [12]	PSO
Generator	b_i	b_i
1	0.027	0.064
2	0.124	0.0105
3	0.292	0.275
4	0.074	0.055
5	0.170	0.150
6	0.170	0.150
Consumer	d_j	d_j
1	0.097	0.080
2	0.077	0.060

Table 3. Bidding Strategy and Profit of Generators and Large Consumers.

	Monte Carlo [12]		PSO	
Generator	P (MW)	Profit ($)	P (MW)	Profit ($)
1	160.0	1368.0	160.0	1370.0
2	89.4	572.7	105.8	588.1
3	45.7	322.9	48.6	324.7
4	88.8	386.4	120.0	429.0
5	43.1	177.5	49.1	181.0
6	43.1	177.5	49.1	181.0
Consumer	P (MW)	Profit ($)	P (MW)	Profit ($)
1	139.7	1126.3	170.5	1162.3
2	112.1	592.6	144.0	621.8
MCP	16.35		16.366	
Total Profit	4723.9		4857.9	

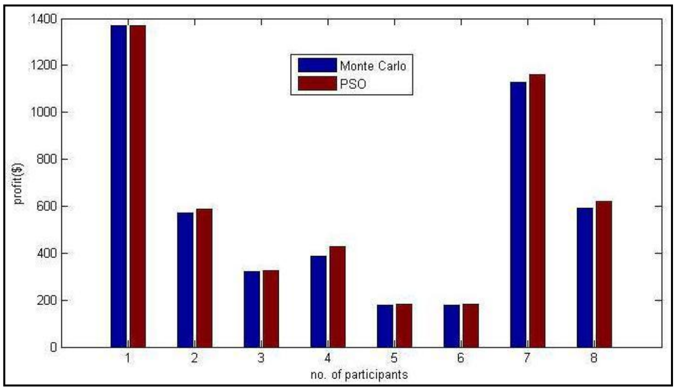

Fig. 3. Expected Profit of Suppliers and Consumers

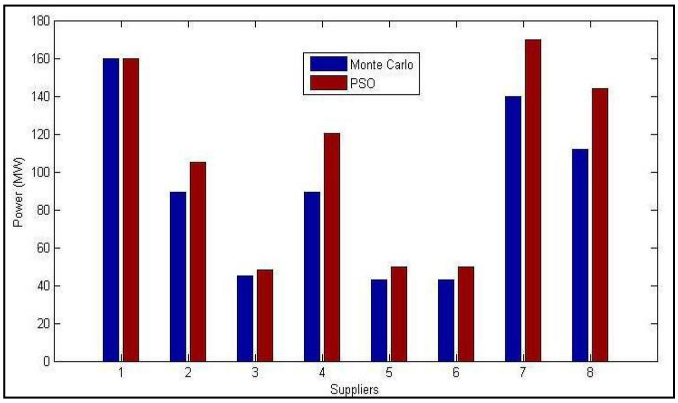

Fig. 4. Expected dispatched Powers of Suppliers.

From the Table 3, it is observed that the profit obtained by each supplier is more in PSO method, when compared with Monte Carlo method. Therefore the bidding strategies obtained by PSO are optimum as compared to Monte Carlo method.

5. CONCLUSION

In this paper Particle Swarm Optimization (PSO) method is used to solve the bidding problem for maximizing the Profits. An example with six suppliers and two large consumers has been used to demonstrate the method, and it has been revealed that the power suppliers can substantially increase their profits by strategic bidding. Also the market clearing price (MCP) can be higher than competitive levels if the suppliers bid strategically.

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