Bidding Strategy Considering Risk by Generating Companies in an Open Electricity Market Using Particle Swarm Optimization

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Abstract- **This paper presents a novel methodology based on Particle Swarm Optimization (PSO) for the preparation of optimal bidding strategies by power suppliers in a competitive electricity market. The gaming by participants in a competitive electricity market causes electricity market more an oligopoly than a competitive market. In general, Competition implies the opportunities for Generation Companies (Gencos) to get more profit and, in the mean time, the risk of not being dispatched. In this paper each participant can increase their own profit by optimally selecting the bidding parameters using PSO. The proposed method is numerically verified through computer simulations on IEEE 30-bus system consist of six suppliers and two large consumers. The results are compared with Genetic Algorithm (GA) and Monte Carlo method. The Test results indicate that the proposed algorithm maximize profit, converge much faster and more reliable than GA and Monte Carlo method**.

Keywords*- *Market Clearing Price; Optimal Bidding Strategy; Fuzzy Inference; Risk Analysis; Particle Swarm Optimization.

I. INTRODUCTION

Recent change in regulatory policies in electricity industries has created competitive environments and markets for power suppliers. Therefore, maximizing the profit, minimizing the risk and gaining the competitive advantage by suppliers are possible through strategic bidding. This paper focuses on market systems based on sealed-bid auctions. An auction is the process of buying and selling certain commodities in a competitive manner. In a market, seller wishes to earn as much profit and a buyer wishes to pay as little as possible. In electricity markets, uniform market clearing price auction is, generally, adopted. Under uniform market clearing price auction, the best strategy of a bidder is to bid at marginal cost, which is less risky. A bidder that bids above the marginal bid has more risk to lose, as it does not know the actual actions of rivals and final market demand. Hence, each bidder must develop an optimal bidding strategy for clearing price auction [1].

A complete review of optimal bidding strategies in Electricity Market (EM) has been published in [1]. David [2] 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. [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 [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. [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 behaviour 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 behaviours 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. Optimal bidding strategy problem using PSO has been applied in[15, 16]. 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 nonconventional (heuristic) methods. Depending on the bidding models, non-differentiable optimization is well established area of the mathematical optimization field with well known conventional, non-heuristic methods. Heuristic methods such as GA, Simulated Annealing (SA) and Evolutionary Programming (EP), PSO have main limitations of their sensitivity to the choice of parameters, such as the intersect and mutation probabilities in GA, temperature in SA, scaling factor in EP etc., [18].

In this paper, a new frame work of developing optimal bidding strategies for Gencos in uniform spot market is presented with associated risks appropriately taken into account. The bids of other competing generators (rivals) are modelled by probability density function. Suppliers bidding decision evaluation is formulated as a stochastic optimization problem and solved using PSO and compared with GA method.

II. PROBLEM FORMULATION

Consider a system consist of '*m*' suppliers and '*n*' large consumers who participate in demand-side bidding. Each supplier and large consumer is required to bid a linear non-decreasing supply and non-increasing demand function to Independent System Operator (ISO). Let for supplier linear supply curve denoted by $G_i(P_i) = a_i + b_i P_i$ where $i= 1, 2 \ldots m$ and for large consumers bid linear demand curve denoted by $W_j(L_j) = c_j - d_j L_j$ where $j=1, 2 \ldots n$. Here P_i is the active power output, a_i and b_i are the bidding coefficients of the i^{th} supplier L_j is the active power load of j^{th} large consumer. c_j and d_j are the bidding coefficients of the j^{th} large consumer; a_i , b_i , c_j and d_j are non-negative.

The main function of ISO is to determine a generation/demand, dispatch/schedule that meets security and reliability constraints using transparent dispatch procedures, with the objective of maximizing total profit. Moreover, when the suppliers and large consumers bid linear supply and demand functions and the network constraints are ignored, maximizing total profit leads to a uniform market clearing price for all suppliers and consumers. 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 Eqs. (1)- (5)

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

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

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

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

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

R is the uniform market clearing price of electricity to be determined. *Q(R)* is the aggregate pool load forecast by PX as follows:

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

$P_{min,i}$ 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, where Q_o 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 Eq. (4) and (5) are ignored, the solution to Eqs. (1) - (3) is:

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

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

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

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)

The objective is to determine a_i and b_i so as to maximize $F(a_i, b_i)$ subject to the constraints Eqs.(1)-(5). $C_i(P_i)$ is the 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)

The objective is to determine c_j and d_j so as to maximize $B(c_j, d_j)$ subject to the constraints Eqs.(1)-(5). $B_j(L_j)$ is the demand (benefit) function of the j^{th} large consumer. In sealed bid auction based electricity market, data for the next hour bidding period are confidential, and hence suppliers and large consumers do not have the information needed to solve the optimization problem with objective function Eqs. (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.

Let, from the i^{th} supplier's point of view, rival's j^{th} ($j \ne i$) 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 Eq. (12) also used for finding optimal bidding coefficients of the large consumers. Based on historical bidding data these distributions can be determined. However, risks associated with building optimal bidding strategies were not taken into account in and will be addressed in this paper as follows:

From the well developed investment theory, it is known that the variance of the potential profit could be used to evaluate the risk of an investment. Following this concept, the problem of building an optimal bidding strategy for the i^{th} Gencos with associated risks taken into account, Eq. (10) could be reformulated as the following stochastic optimization problem:

$$F(a_i,b_i)=(1-\lambda)E(F)-\lambda D(F) \qquad (13)$$

Subjected to

$$P_{\min,i} \le ((E(R)-a_i)/b_i \le P_{\max,i} \quad (14)$$

where $E(F)$ and $D(F)=\{Var(F)\}^{1/2}$ are the expected value and standard deviation of the profit and $E(R)$ the expected value of MCP. $0 \le \lambda \le 1$ is a risk coefficient used to represent the degree of risk averseness of the i^{th} Genco. $\lambda= 0$ corresponds to the situation that the objective is to maximize profit only without consideration of risks, and this is what has been done in [12]. $\lambda= 1$ represents the other extreme where risk minimization is the unique objective. Generally, a Genco should well balance these two conflicting objectives: profit maximization and risk minimization. The strategy used to balance these two objectives can be reflected by the value of λ specified. Hence the problem of building strategy for the i^{th} Genco with risk management can be described as: for a given risk coefficient λ determine bidding coefficient a_i and b_i as to maximize $F(a_i, b_i)$ subject to Eq. (14).

Using probability density function Eq. (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 Eq.(13) with constraint Eq. (14) and Eq.(11) with constraints Eqs. (1)-(5) becomes a stochastic optimization problem.

In this paper, PSO is used to solve the optimal bidding strategy problem and results are compared with GA. In this work, a_i and c_j are fixed and the values of b_i and d_j are searched through PSO method. PSO method is very efficient to solve the above stochastic optimization problem, presented in the following section.

III. SOLUTION ALGORITHM

PSO is similar to the other evolutionary algorithms in that the system is initialized with a population of random solutions. Each potential solution, call particles, flies in the *D*-dimensional space with a velocity which is dynamically adjusted according to the flying experiences of its own and its colleagues [13]. The location of the i^{th} particle is represented as $X_i = (x_{i1}, x_{i2}...x_{iD})$. The best previous position of the i^{th} particle is recorded as P_{besti}. The index of the best, P_{best} among all the particles is represented by the symbol g. The location P_{bestg} is also called G_{best}. The rate of velocity for the i^{th} particle is represented as $V_i = (v_{i1}, v_{i2}...v_{iD})$. The modified velocity and position of each particle are calculated using current velocity and the distance from P_{best} to G_{best} as Eqs. (15) and (16).

$$V_r^{k+1} = w^k V_r^k + c_1 rand_1 * (P_{best}^k - X_r^k) + c_2 rand_2 * (G_{best}^k - X_r^k) \quad (15)$$

$$X_r^{k+1} = X_r^k + V_r^{k+1} \quad (16)$$

Where k is the iteration counter and kmax is the maximum iteration number.

A. PSO algorithm for bidding problem

The optimal bidding problem formulated in the previous section, each particle is composed of the strategic variable. For the supplier considered in linear bid model using probability density function the position of *r* represents the optimum value of b_i and d_j. For each generated particle, profit maximization objective function Eq. (10) is taken as fitness function. $P_{best\ r}$ represents the best position of the particle *r* and the best position reached by the swarm G_{best} in the final iteration gives optimal value of strategic variable. The computational steps for searching bidding coefficients using FAPSO algorithm are described below.

Step-1: The initial population and initial velocity for each particle should be generated randomly.

Step-2: The objective function is to be evaluated for each individual.

Step-3: The individual that has the minimum objective function should be selected as the global position.

Step-4: The r^{th} individual is selected.

Step-5: The best local position (*Pbest*) is selected for the r^{th} individual.

Step-6: Calculate the next position for each individual based on the FAPSO parameters and Eq. (15) and then checked with its limit.

Step-7: If all individuals are selected, go to the next step, otherwise $k=k+1$ and go to Step 4.

Step-8: If the current iteration number reaches the predetermined maximum iteration number, the search procedure is stopped, else go to Step 2.

The last *Gbest* is the solution of the problem. The flow chart of the proposed method is shown in Fig.1.

IV. RESULTS AND DISCUSSIONS

In order to evaluate the performance of proposed method for solving optimal bidding problem, IEEE 30-bus system is considered. In this work, the parameters used for PSO and GA are given in Table I. Computer Configuration: 1.66GHz, core 2 duo processor, 3GB RAM and MATLAB 7.8 version is used. *c1*, *c2* learning factors; *w* inertia weight for PSO; P_e

elitism probability; P_c crossover probability; P_m mutation probability; l chromosome length for GA.

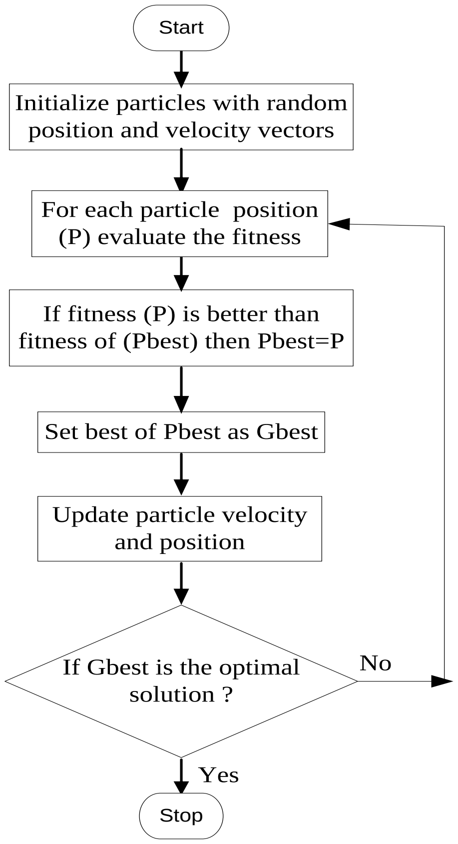

Fig. 1 Flow chart of the proposed PSO

TABLE I PARAMETERS USED FOR DIFFERENT APPROACHES

PSO	GA
No. of particles= 40; Max. iterations=100; $c1$=2.5,$c2$=2.5; w=1.0 to 0.5	Population = 40; Generations=100; P_e =0.1; P_c=0.8; P_m=0.001, l=16

A. Optimal Bidding without Considering Risk Coefficient (λ)

The IEEE 30-bus system consists of six suppliers and two large consumers. The Generator and large consumer data are taken from [12]. Q_o is 300 and K is 5 for aggregated load. Using PSO, bidding coefficients are shown in Table II, and generation outputs, market clearing price and profit of six suppliers and two large consumers are shown in Table III.

The superiority of the PSO approach is demonstrated through comparison of simulation results with GA. Owing to the randomness in all the approaches, the algorithms were executed 10 times when applied to the example data. The best, worst, average value, total profit and average c.p.u time over a period found by all the methods are tabulated in Table IV. The Percentage Deviation (PD) is defined as (Best-Worst)/Best*100.

The Result shows that the proposed PSO maximizes total profit compared to GA. Thus, it conforms that the PSO is well capable of determining the global or near global optimum bidding strategy. Moreover PSO shows good consistency by keeping the variation between the best and worst solution within 0.044%. The average c.p.u time for PSO is less when compared to GA. This shows the superiority of PSO, because PSO has better sharing and conveying mechanism than GA and also better dynamics of balance between global and local search abilities than GA.

TABLE II BIDDING STRATEGIES FOR GENERATORS AND LARGE CONSUMERS

	PSO	GA	Monte Carlo [12]
Generator	b_i	b_i	b_i
1	0.1064	0.0698	0.00292
2	0.4967	0.3259	0.1242
3	1.3009	0.8535	0.2923
4	0.2395	0.1571	0.0743
5	0.7096	0.4655	0.1705
6	0.7096	0.4655	0.1705
Large Consumer	d_j	d_j	d_j
1	0.3784	0.3623	0.3623
2	0.2838	0.2741	0.2741

TABLE III MCP ($/MWH) AND PROFIT ($) OF GENERATORS AND LARGE CONSUMERS

	PSO		GA		Monte Carlo [12]	
Generator	P	Profit	P	Profit	P	Profit
1	160	2590.6	160	2146.3	160	1368.0
2	37.9	632.3	48.9	656.0	89.4	572.7
3	20.0	364.8	21.3	326.0	45.7	322.9
4	59.4	757.1	72.9	701.4	88.8	386.4
5	21.2	283.2	26.2	268.8	43.1	177.5
6	21.2	283.2	26.2	268.8	43.1	177.5
Large consumer	L	Profit	L	Profit	L	Profit
1	15.8	85.3	35.3	260.77	139.7	1126.3
2	3.5	3.2	20.3	64.55	112.1	592.6
MCP	23.99		21.21		16.35	
Total Profit	4999.92		4692.83		4723.9	

TABLE IV PERFORMANCE COMPARISON OF PSO AND GA

		PSO	GA
Total Profit	Best($)	4999.92	4692.83
	Worst($)	4654.72	4246.28
	Ave.($)	4827.32	4469.55
	PD (%)	0.069	0.095
Ave. c.p.u time (sec)		40.11	45.76

B. Optimal Bidding under A GDiven Risk Coefficient (λ)

In order to observe the profit by taking risk coefficient for the same bidding problem, consider one of the suppliers among six suppliers and vary the risk coefficient. For different values of λ simulation results are listed in Table V, including optimal bidding coefficients b_2, expected dispatched Level P_2, expected market clearing price R as well as expected value and variance of the profit.

TABLE IV SIMULATION RESULTS UNDER DIFFERENT Λ'S

λ	*b_2*	*P_2(MW)*	*R*	*E(F)*	*D(F)*
0	0.5256	36.65	24.40	636.46	53.5852
0.3	0.5189	36.79	24.34	634.72	53.2146
0.5	0.4116	42.23	22.63	628.84	52.4027
0.7	0.2705	49.57	18.66	535.76	46.8245
0.9	0.1391	91.29	17.94	524.61	40.2172
0.9335	0.0964	130.00	17.78	520.82	36.5634

When λ varies from 0 to 0.9, there are only a little change in the optimal bidding coefficient b_2, expected dispatched Level P_2, expected market clearing price R, as well as expected value and variance of the profit. But when λ varies from 0.9 to 0.9335, significant changes of these quantities are observed. This is because when λ increases from 0.9 to 0.9335, the dispatched generation level of rival is beyond its lower limit and hence the rival quits from the competition. Suppose that the estimations of the second Genco about the expected value of rivals' bidding coefficients as shown in [12] are actually 15% above their actual bidding pricing, and other parameters remain unchanged. In this case, if we set λ=0.9 (i.e. risk is not taken into consideration), the optimal bidding strategy thus obtained for the second Genco is b_2=0.52256. In fact, since the actual bidding prices of rivals are lower than expected, the second Genco cannot be dispatched. Hence, it is necessary for Genco to make risk management in developing optimal bidding strategies.

V. CONCLUSIONS

In this paper, application of PSO has proposed for optimal bidding strategy for suppliers and large consumers with and without risk coefficient in an open electricity market. Rivals bidding prices have been represented as stochastic variables with probability density function. In this approach, each participant tries to maximize their profit with the help of information announced by system operator. Simulation results of a numerical example have demonstrated that bidding decision without consideration of risks may lead to financial losses to Gencos. The PSO approach has several advantages over the other approaches. The superiority of PSO has been successfully tested on IEEE 30-bus system and compared with GA for single hourly demand with and without risk constraint. The simulation result shows the feasibility and robustness of the PSO approach as an efficient tool to find optimal bidding strategy of Gencos in an open electricity market.

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