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Modeling of bidding Strategies for Power Suppliers and Large Consumers in Electricity Market with Risk Analysis

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Abstract*— *In the competitive electricity market, Generation companies and large consumers are participating in bidding methodologies for their own benefits. In oligopoly market structure, GENCOs tries to maximize their profit and minimize the risk factor. So it is very essential and important for the GENCOs to formulate optimal bidding strategies with risk terminology before entering into the electricity market to achieve a maximum profit , since the market clearing price (MRP) are variable in nature.

***In this paper an optimal bidding strategy associated with risk management is devised as a multi objective stochastic optimization problem and solved by Quantum inspired PSO. The impact of risk on the GENCOs is analyzed by introducing the factor λ. The proposed Quantum inspired PSO effectively maximize the GENCOs profit and benefit of large consumers. A numerical example with six suppliers and two large consumers is considered to illustrate the essential features of the proposed method and test results are tabulated. The simulation result shows that these approaches effectively maximize the Profit and Benefit of Power suppliers and Large Consumers, converge much faster and more reliable when compared with existing methods*.**

***Index Terms*— *Electricity market, Optimal bidding, Profit maximization, Risk analysis, Quantum inspired PSO*.**

I. INTRODUCTION

The deregulation of the power industry across the world has greatly increased market competition by reforming the traditionally integrated power utility into a competitive electricity market, which essentially consists of the day-ahead energy market [1] and [2], real-time energy market and ancillary services market. Therefore, in a deregulated environment, GENCOs are faced with the problem of optimally allocating their generation capacities to different markets for profit maximization purposes. Moreover, the GENCOs have greater risks than before because of the significant price volatility in the spot energy market introduced by deregulation..

Bidding strategies are essential for maximizing profit and have been extensively studied [3–6]. Usually, optimal bidding strategies is based on the GENCOs own costs, anticipation of other participants bidding behaviors and power system operation constraints. The PoolCo model is a widely employed electricity market model [1]. In this model GENCOs develop optimal bidding strategies, which consist of sets of price–production pairs. The ISO implements the market clearing procedure and sets the MCP [7]. Theoretically, GENCOs should bid at their marginal cost to achieve profit maximization if they are in a perfectly competitive market. However, the electricity market is more akin to an oligopoly market and GENCOs may achieve benefits by bidding at a price higher than their marginal cost. Therefore, developing an optimal bidding strategy is essential for achieving the maximum profit and has become a major concern for GENCOs. Identifying the potential for the abuse of market power is another main objective in investigating bidding strategies.

The bidding strategy problem is developed by many researchers [2–18]. They used different methods such as Game theory approach [8], novel stochastic optimization model [9], Lagrangian relaxation [10]**,** Genetic Algorithm [11-12], Evolutionary programming [13] and Particle swarm optimization [13-15]**,** to solve the optimal bidding strategy problem. Monte Carlo Simulation is one of these methods [16-18]. It repetitively computes the optimal bidding strategy for one player with randomly rival bidding. Reinforcement Learning is one else method to solve the optimal bidding strategy problem [19-20]. In this method, next bidding price will be determined by artificial agent in each round of the auction. This chosen price corresponds to load forecast and previous experience. All the above methods have their own advantages and also disadvantages.

In this paper, the bidding strategy problem is modeled as an optimization problem and Quantum inspired Particle Swarm Optimization (QPSO) is used to solve the bidding strategy. A numerical example with six suppliers and two large consumers is used to illustrate the essential features of the proposed method. Comparative studies with genetic algorithm (GA) and Monte Carlo method have also been made to analyze the bidding coefficients, power, load, profit and benefit of Electricity Producers and large consumers. The test results indicate that the proposed method improves the profit and benefit, converge much faster and more reliable than available methods.

II. MARKET STRUCTURE AND OPERATIONS

A Pool Co based market structure is defined as a centralized market place that clears the market for buyers and sellers [1-2]. Electric power sellers/buyers submit bids to the pool for the amounts of power that they are willing to trade in the market. Sellers in a power market would compete for the right to supply energy to the grid, and not for specific customers. If a market participant bids too high, it may not be able to sell. On the other hand, buyers compete for buying power, and if their bids are too low, they may not be able to purchase. In this market, low cost generators would essentially be rewarded.

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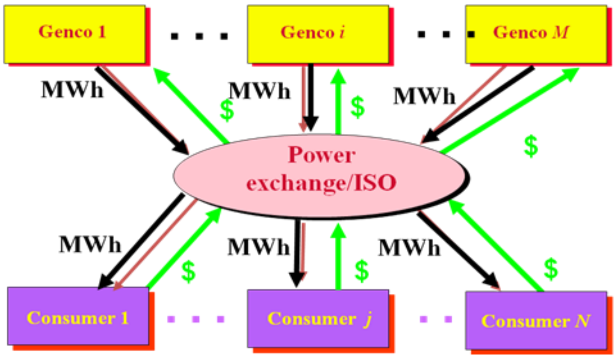

Fig. 1. Market structure

An ISO within a Pool Co would implement the economic dispatch and produce a single (spot) price for electricity, giving participants a clear signal for consumption and investment decisions. The market dynamics in the electricity market would drive the spot price to a competitive level that is equal to the marginal cost of most efficient bidders. In this market, winning bidders are paid the spot price that is equal to the highest bid of the winners.

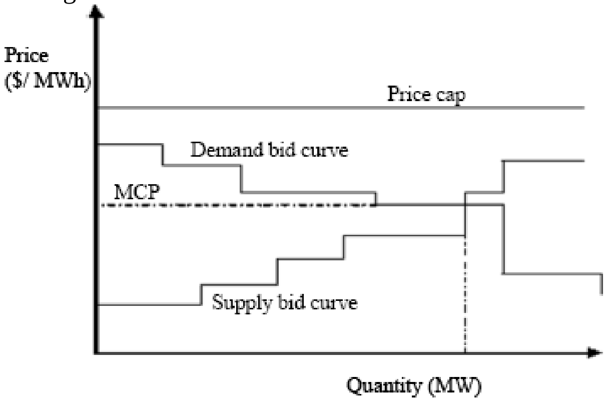

Fig. 2. Market equilibrium point

Power exchange (PX) accepts supply and demand bids to determine a MCP for each of the 24 periods in the trading day [2]. Computers aggregate all valid supply bids and demand bids into an energy supply curve and energy demand curve. MCP is determined at the intersection of the two curves, and all trades are executed at the MCP, in other words MCP is the balance price at the market equilibrium for the aggregated supply and demand graphs. Generators are encouraged to bid according to their operating costs because bidding lower would lead to financial losses if MCP is lower than the operating cost and bidding higher could cause units to run less frequently or not run at all.

III. PROBLEM FORMULATION

A. Mathematical Model

Let m Independent Power Producers (IPPs) bid linear supply curve denoted by *R= ai+Pibi* when *i*=1, 2… m and n large consumers bid linear demand curve denoted by *R=cj-djLj* when *j*=1, 2… n. *P* and *L* are power generation and consumption respectively. *R* is market clearing price (MCP). PX will receive bid from all market participants. Using predicted aggregate load from small users, PX/ISO will determine MCP that will balance the energy demand and supply

The objective of electricity producers is to maximize its profit. Suppose the power producer *i* has cost function denoted by

$$C_i(P_i) = e_i P_i + f_i P_i^2 \tag{1}$$

The objective function of power producer can be defined as:

$$Max: F(a_i, b_i) = RP_i - C_i(P_i) \tag{2}$$

Similarly, the objective of large consumer is to maximize its benefit. Suppose the large consumer j *has* revenue function denoted by

$$B_j(L_j) = g_j L_j - h_j L_j^{\,2} \tag{3}$$

The objective of large consumer can be defined as:

$$Max: G(c_j, d_j) = B_j(L_j) - R_j L_j \tag{4}$$

Market Clearing Price (R) represented by the following equation

$$R = \frac{Q_0 + \sum_{i=1}^{m} \frac{a_i}{b_i} + \sum_{j=1}^{n} \frac{c_j}{d_j}}{K + \sum_{i=1}^{m} \frac{1}{b_i} + \sum_{j=1}^{n} \frac{1}{d_j}} \tag{5}$$

The aggregated load demand formulated as follows

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

Constraints

1. Power balance constraints:

$$\sum_{i=1}^{m} P_i = Q(R) + \sum_{j=1}^{n} L_i \tag{7}$$

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

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

2. Power generation limit constraints:

$$p_{i\min} \le p_i \le p_{i\max} \qquad i = 1,2.....n \tag{10}$$

3. Power consumption limit constraints:

$$L_{j\min} \le L_j \le L_{j\max} \qquad j = 1,2.....n \tag{11}$$

Where

$F(a_i, b_i)$ Profit of i^{th} electricity producer

$G(c_j, d_j)$ Benefit of j^{th} large consumer

$C_i(P_i)$ Cost function of i^{th} electricity producer

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$B_j(L_j)$	Revenue function of j^{th} large consumer
P_i	Output power of i^{th} electricity producer
L_j	Load power of j^{th} large consumer
$Q(R)$	Aggregated load demand
Q_o	Constant number of aggregated load demand
K	Price elasticity of the aggregate Demand
P_{imax}	Maximum output limits of unit *i*.
P_{imin}	Minimum output limits of unit *i*.
$L_{j\max}$	Maximum Power consumption limit of Consumer *j*
$L_{j\min}$	Maximum Power consumption limit of Consumer *j*
N	No of generating units
a_i, b_i, c_i	Cost co-efficient of the i^{th} generator

B. Development of bidding strategy

Generally GENCOs do not have access to know the complete information of their opponent, so it is necessary for a GENCO to estimate opponents' unknown information. It is assumed that the past data of bidding coefficients are available. The i^{th} GENCO can determine mean and standard deviations of bidding coefficients based on historical data. Suppose that the data of bidding coefficients are normally random variables with the following probability density function (pdf) as follows:

$$pdf(x_i) = \frac{1}{\sqrt{2\pi\sigma_i}} \exp\left(-\frac{(x_i - \mu_i)^2}{2\sigma_j^2} \right) \tag{12}$$

Where,

σ_i - is the standard deviation

μ_i - is the mean values

The data of bidding coefficients have two values a_j and b_j of bidding price function, respectively. The *pdf* function with two variables that represents the joint distribution of $a_j^{(t)}$ and $b_j^{(t)}$ $(j=1,2,\ldots\ldots n,\ j\neq i;\ t= 1 \text{ to } 24)$ can be formulated as:

$$pdf(a_i,b_i) = \frac{1}{2\Pi\sigma_j^{(a)}\sigma_j^{(b)}\sqrt{1-\rho_j^2}} \times$$
$$\exp\left\{ -\frac{1}{2(1-\rho_j^2)} \left[\left(\frac{a_j - \mu_j^{(a)}}{\sigma_j^{(a)}} \right)^2 \right.\right. \tag{13}$$
$$\left.\left. -\frac{2\rho_j(a_j - \mu_j^{(a)})(b_j - \mu_j^{(b)})}{\sigma_j^{(a)}\sigma_j^{(b)}} + \left(\frac{b_j - b_j^{(b)}}{\sigma_j^{(b)}} \right)^2 \right] \right\}$$

Where the

' ρ_j' is the correlation co efficient 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 distribution of a_j and b_j are 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. Using probability density function(12) for suppliers 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 equation(2)and (4) and constraints (7) to (11) becomes a stochastic optimization problem, presented in following section.

The correlation coefficient is a number among -1 and 1. If there is no relation of two variables, the correlation coefficient is 0. The perfect relations of two variables, the correlation coefficient is 1 or -1.

Based on estimation of bidding coefficients, the ith GENCO can determine $a_j(t)$ and $b_j(t)$ so as to maximize the profit. Optimal bidding became a stochastic problem.

C. Risk Analysis

The function of power suppliers is to deliver power to a large number of consumers. However the demands of different consumers vary in accordance with their activities. The changes in demand shows that load on a power companies never constant, rather it varies from time to time. Most of the complexities of modern power companies operation arise from the inherent variability of the load demanded by the users. Because of these load fluctuations and nature of participants each GENCO is subjected to market risk. So, while making bidding strategies these risk factors also be considered to maximize the profit of GENCOs. It is experienced from the probability theory, the role of variance of the profit is used to estimate the risk of the day ahead investment. Based on this methodology, the proposed optimal bidding strategy for the i^{th} GENCO with its operational risk may be formulated as

Maximize

$$F(a,b) = (1-\lambda)E(F) - \lambda D(F) \tag{14}$$

Subject to

$$P_{i\min} \leq \frac{(E(R) - a_i)}{b_i} \leq / P_{i\max} \tag{15}$$

Where

$E(F)$ - Expected value of the profit

$D(F)$ - Standard deviation of the profit

$E(R)$ - Expected value of market clearing price

λ- Risk factor

λ is referred as a risk factor and is used as a scale to measure the impact of risk on the GENCO and it can be varied from 0 to 1.There is no risk for a company when λ is equal to zero. As a result, the company yields maximum profit. Rather, if λ is equal to one then the company is under minimum risk. So in this condition, the prime objective is to minimize the risk. Normally, the power producers should study and balance these two conflicting parameters such as profit maximization and risk minimization. The methodology developed to balance these two parameters depends upon the value of λ. In this paper, an elegant approach for improving the profit of GENCO by including the various degree of risk factor is suggested. Hence there are two bidding coefficients (a_i, b_i).

By keeping a_i as constant and b_i is varied till the system reaches its maximum profit. The best coefficient b_i is identified by solving the problem with the help of QPSO.

IV. PROPOSED METHODOLOGY

A. Quantum inspired particle swarm optimization (QPSO)

The identification and selection of best bidding coefficients (b_i and d_j) is accomplished by using Quantum inspired PSO, so as to maximize the profit and benefit of power producers and large consumers in pool based energy market.

The Quantum inspired particle swarm optimization (QPSO) is one of the recent optimization technique introduced by Sun in 2004 [21-22] which is based on quantum mechanics. Like any other evolutionary algorithm, a quantum inspired particle swarm algorithm relies on the representation of the individual, the evolutionary function and the population dynamics. The particularity of quantum particle swarm algorithm stems from the quantum representation it adopts which allows representing the superposition of all potential solutions for a given problem. QPSO has stronger search ability and quicker convergence speed since it not only introduces the concepts of quantum bit and rotation gate but also the implementation of self-adaptive probability selection and chaotic sequence mutation. Definition of quantum bit, the smallest unit in the QPSO, is defined as a pair of numbers

$$\begin{bmatrix} \alpha_{jt}(t) \\ \beta_{jt}(t) \end{bmatrix} \quad \begin{cases} j = 1,2....,m \\ i = 1,2......,n \end{cases} \tag{16}$$

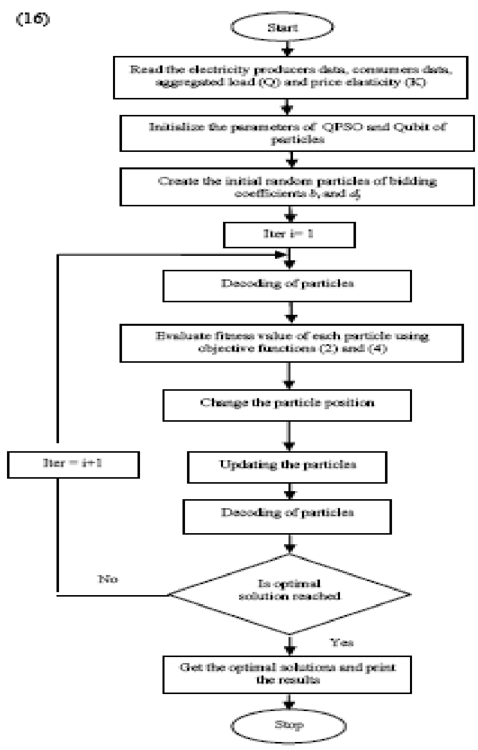

Fig . 3. Flow chart for proposed method

The modulus $|\alpha_{ji}(t)|^2$ and $|\beta_{ji}(t)|^2$ give the probabilities that the quantum bit exists in states "0" and "1", respectively, which must satisfy

$$|\alpha_{ji}(t)|^2 + |\beta_{ji}(t)|^2 = 1 \tag{17}$$

A string of quantum bits consists of quantum bit individual, which can be defined as

$$q_j(t) = \begin{bmatrix} \alpha_{ql}(t),....,\alpha_{ji}(t),....,\alpha_{jn}(t) \\ \beta_{jl}(t),....,\beta_{ji}(t),....,\beta_{jn}(t) \end{bmatrix}$$

$$= [q_{jl}(t),......,q_{ji}(t),.....,q_{jn}(t)] \tag{18}$$

A quantum bit is able to represent a linear superposition of all possible solutions due to its probabilistic representation. As a result, totally 2n kinds of individual can be represented by combination of different quantum bit states. This quantum bit representation has better characteristic of generating diversity in population than other representations.

The quantum bit individual can be represented in the form of quantum angles.

$$\begin{aligned} q_j(t) &= [q_{jl}(t),....,q_{ji}(t),...,q_{jn}(t)] \\ \theta_j(t) &= [\theta_{jl}(t),....,\theta_{ji}(t),...,\theta_{jn}(t)] \end{aligned} \tag{19}$$

B. Decoding of particles

When a particle collapse into a basic state, the probability of occurrence of the basic state need be expressed to participle in the fitness assessment of particles. Supposed the actual parameter space searched by algorithm is [a, b], and the occurred probability of some state is [0,1], then the probability needed to be decoded into the actual parameter space [a,b]. The decoding process can expressed by

$$\begin{cases} S(j,q) = p(2,q,j)^2 * (b-a) + ar < p \\ s(j,q) = p(1,q,j)^2 * (b-a) + ar \geq p \end{cases} \tag{20}$$

Where p is the choice probability of state expression; r is random number from 0 to 1; p(1, q, j) expression $\propto$ of 9th dimension of jth particle. S(j,q) denotes actual parameter values of qth dimension of jth particle..

C. Updating particles

The main idea of QPSO is to update the particle position represented as a quantum angle θ. The common velocity update equation in conventional PSO is modified to get a new quantum angle which is translated to the new probability of the Qubit by using the following formula.

Power suppliers	QPSO (proposed)	GA	MONTE CARLO
1	0.0811	0.058	0.0297
2	0.1100	0.101	0.124
3	0.2641	0.221	0.292
4	0.1976	0.035	0.074
5	0.1149	0.116	0.170
6	0.0878	0.116	0.170

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$$\Delta\theta_{jq}^{t+1} = \omega \times \Delta\theta_{jq}^{t} + C_1.rand1.(\theta_{bjq} - \theta_{jq}^{t}) + C_2.rand2.(\theta_{gq} - \theta_{jq}^{t}) \quad (21)$$

Where;

$\Delta\theta_{jq}^{t}$	angle changes of q^{th} dimension of j^{th} particle
ω	inertia weight
C_1 , C_2	acceleration factors
rand1, rand2	random numbers from 0 to 1
θ_{bjq}	local best angles
θ_{gq}	global best angles of q^{th} dimension

According to the angle changes, the matrix expression of the quantum rotation gate can be described by

$$\begin{bmatrix} \cos\Delta\theta_{jq}^{t+1} & -\sin\Delta\theta_{jq}^{t+1} \\ \sin\Delta\theta_{jq}^{t+1} & +\cos\Delta\theta_{jq}^{t+1} \end{bmatrix} \quad (22)$$

Where $\Delta\theta_{jq}^{t+1}$ denotes angle changes of qth dimension of j^{th} particle in the t+1th iterative course; In the next step, probability amplitudes of q^{th} dimension of j^{th} particle in t+1th iterative course can be updated according rotation g.

V. CASE STUDY AND RESULTS

The proposed method has been applied to a test system [4] which consists of six Electricity Producers and two large consumers participating in an electricity market. The production cost coefficients and output limits of all six Electricity Producers and two large consumers are listed in Table-1 and Table-2.

TABLE 1
DATA FOR ELECTRICITY PRODUCERS

Power suppliers	e (\$/h)	f (\$/MWh)	P_{imin} (MW)	P_{imax} (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

TABLE 2
DATA FOR LARGE CONSUMERS

Large Consumers	g (\$/h)	h (\$/MWh)	P_{imin} (MW)	P_{imax} (MW)
1	30	0.04	0	200
2	25	0.03	0	150

The fuel cost of each generator is expressed by quadratic equation. The parameters associated with the load characteristics are considered from the reference [4] where in Q_0 = 300MW and K= 5.

TABLE 3
BIDDING COEFFICIENTS OF POWER SUPPLIERS

	QPSO (proposed)	GA	MONTE CARLO
MCP (\$)	16.46	15.81	16.35
TOTAL PROFITS (\$)	4825.67	4554.20	4723.90

TABLE 4
BIDDING COFFICIENTS OF LARGE CONSUMERS

Power suppliers	QPSO (proposed)		GA		MONTE CARLO	
	P (MW)	Profit (\$)	P (MW)	Profit (\$)	P (MW)	Profit (\$)
1	160.00	1385	152.00	1310.1	160.00	1368
2	90.00	593.65	102.83	504	89.4	572.7
3	45.00	327.26	41.921	291.8	45.7	322.9
4	91.00	400.94	116.28	384.7	88.8	386.4
5	42.00	181.02	46.025	165.8	43.1	177.5
6	42.00	181.02	46.025	165.8	43.1	177.5

The feasible parameters obtained by systematic process for QPSO are as follows. Population size = 40; Acceleration Coefficients are 0.5 and 1.25 respectively. Inertia weight ω = 0.72 and maximum number of iterations = 500. The proposed QPSO methodology is tested to demonstrate its superior performance on six Electricity Producers and two large consumers using MATLAB.

TABLE 5
OUTPUT POWERS AND PROFITS OF ELECTRICITY PRODUCERS

Large Consumers	QPSO (proposed)		GA		MONTE CARLO	
	L (MW)	Benefit (\$)	L (MW)	Benefit (\$)	L (MW)	Benefit (\$)
1	200	1200	162.61	1135.6	139.7	1126.3
2	51	556.18	139.95	596.4	112.1	592.6

TABLE 6
OPTIMAL LOAD DEMAND AND BENEFITS OF LARGE CONSUMERS

Risk factor (λ)	R	$E(F)$	$D(F)$	Profit
0	16.46	593.65	41.8500	593.65
0.3	16.40	591.91	41.5194	401.88
0.5	14.70	586.03	40.7075	272.66
0.7	10.73	492.95	35.1293	123.29
0.9	10.01	481.18	28.5220	22.45
0.9335	9.84	477.45	24.8682	8.8359

The simulation results of bidding coefficients of six power suppliers and two large consumers are presented in Table – 3 and Table -4. The optimal output power and profit of six power suppliers are given in Table – 5. Table – 6 elaborates optimal load demand and benefit of two large consumers. Also, market clearing price and total profits of power suppliers and large consumers are presented in Table – 7.The profit of GENCOs with different percentage of risk are analyzed and displayed in Table - 8.

Comparative studies with genetic algorithm (GA) and Monte Carlo method have also been made to analyze the bidding coefficients, power, load, profit and benefit of six power suppliers and two large consumers. From the results, it is clear that the proposed method provides maximum profits and benefits compared to existing methods. Also, the computational time of the proposed method is much reduced.

VI. CONCLUSION

In this paper, QPSO is applied to solve bidding strategy in order to improve the profit and benefit of Power suppliers and large consumers associated with risk management in an open electricity market. In this approach, each participant tries to maximize their profit with the help of information announced by system operator. The simulation result has been compared with Genetic Algorithm (GA) and Monte Carlo method. The results obtained from the proposed method exhibit the maximization of profits and benefits over the other methods. 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. This results show that QPSO approach is a promising technique for solving complicated power system optimization problem under deregulated environment.

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