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Research Article

Application of Firefly algorithm for solving Strategic bidding to maximize the Profit of IPPs in Electricity Market with Risk constraints

Asokan K[Å*] and Ashok Kumar R[Å]

[Å]Department of Electrical Engineering, Annamalai University, Tamil Nadu, India, 608002

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Abstract

The renovation of electric power systems plays a major role on economic and reliable operation of power system. Generation companies and tail end customers are undergoing a major multiple task of designing of proper operating methodologies. Therefore an exhaustive formulation of optimal bidding strategy becomes a subject of mater of generation companies and end consumers. In this paper an innovative approach for defining optimal bidding strategy is presented as a stochastic optimization problem and solved by Firefly algorithm.(FA). The Firefly Algorithm is a Meta heuristic, nature inspired, optimization algorithm which is based on the social flashing behavior of fireflies and has been introduced for the bidding problem to obtain the global optimal solution. The proposed Firefly algorithm effectively maximizes the GENCOs profit and benefit of large consumers. The impact of risk on the GENCOs is analyzed by introducing the factor λ. The proposed Firefly algorithm effectively maximizes the GENCOs profit. A numerical example with six suppliers 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 of Power suppliers, converge much faster and more reliable when compared with existing methods..

Keywords: *Electricity market, optimal bidding, Profit maximization, risk analysis, Firefly algorithm*.

1. 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 (Mohammad Shahidehpour, *et al* 2000), 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 (Dhanalakshmi, S *et al* 2011). 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 (Mohammad Shahidehpour, *et al* 2000). 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 (Gountis, V.P *et al* 2004). 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.

In general, strategic bidding is an optimization problem and has been discussed by many researchers in their literatures. It can be found that the researcher have solved the bidding problem by conventional and non-conventional (heuristic) techniques. Dynamic programming (Wen, F.S *et al* 2004), Monte carlo (David, A.K *et al* 2001), game theory (Rajkumar, *et al* 2004), (Eng Zhao *et al* 2010). Mixed integer linear programming (Guan,

X *et al* 2001) and lagrangian relaxation (Daoyuan zhang *et al* 2000) are the examples of conventional methods. Bidding problem was addressed for the first time by David, A.K (2001) . In this work, a conceptual optimal bidding model was developed and solved by Dynamic programming technique for England-Wales electricity markets. Here each supplier is required to bid for a constant price for each block of generation. System demand variations and unit commitment costs were also considered in the model. Wen and David (2004) have

*Corresponding author: **Asokan K**

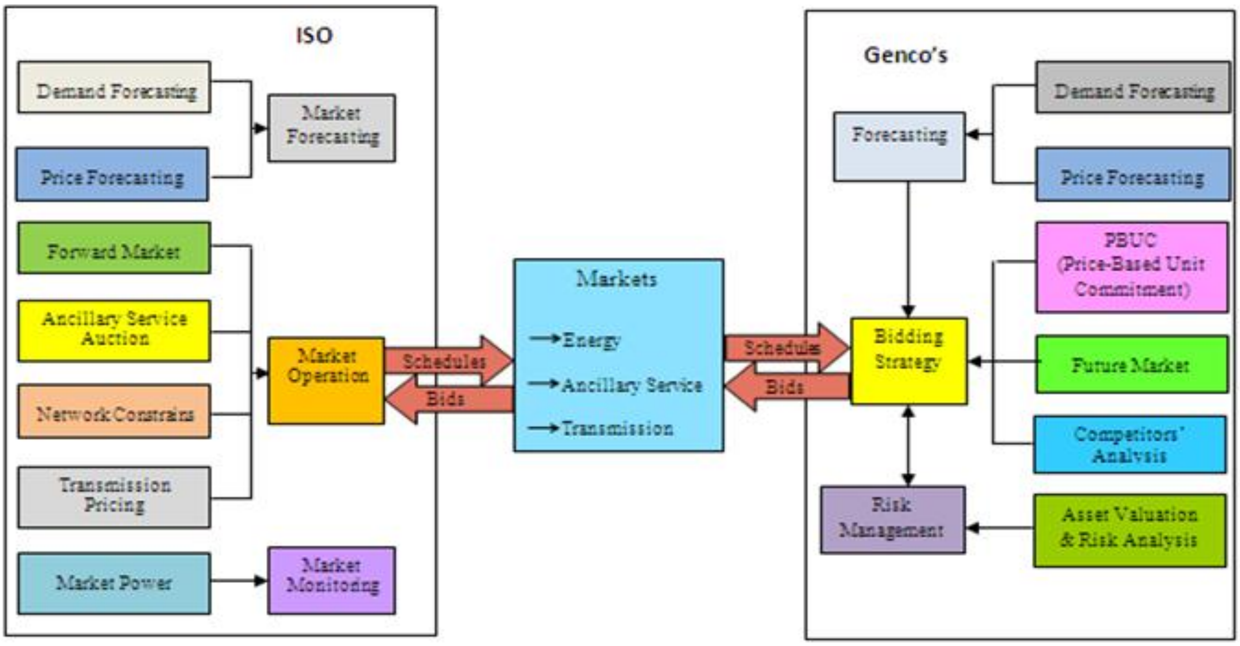

Fig.1 Market Structure

described the strategic bidding as a stochastic optimization problem and it is solved by using Monte Carlo method for single period action. An importance is given to competitive generators and large consumers while maximizing their own benefits. Game Theory and non game theory based bidding strategies are another approach and are briefly explained in references (Rajkumar, *et al* 2004, Eng Zhao, *et al* 2010). Here, the competition among participants is modeled as a non-cooperative game with incomplete information. The imperfect information of the suppliers is analyzed by game theory and Nash equilibrium has been identified. In (De la Torre, S *et al* 2002, Bakirtzis, A.G *et al* 2007, Conejo, A..J *et al* 2002), a mathematical method based on Mixed Integer Linear Programming (MILP) is suggested. Here an appropriate forecasting tool is used to estimate the probability density function of next day hourly market clearing price. This probabilistic information is used to formulate the self scheduling profit maximization problem. Lagrangian relaxation (LR) method is applied in (Daoyuan zhang *et a*l 2000)) and (Somgiat Dekrajanjpetch *et al* 1999) for solving optimization-based bidding and self-scheduling where a utility bids part of its energy and self-schedules the rest as in New England. The model considers ISO bid selections and uncertain bidding information of other market participants. In some cases it is difficult to formulate a mathematical model using objective function and constraints. Under these circumstances conventional methods may not be suitable for solving bidding problem.

Heuristic methods are different methodology, which provides best solution through its global searching behavior. It includes Genetic Algorithm (GA), Simulated Annealing (SA), Evolutionary Programming (EP), Particle Swarm Optimization (PSO) and Hybrid approaches among them. In reference (Yamin, H.Y *et al* 2004) & (Azadeh, A *et al* 2012), an optimal bidding strategy for the power suppliers are framed as a optimization problem and it is solved by GA. A method to analyze the optimal bidding strategy of generation companies including the emission constraint is discussed in (Rocio Herranz, *et al* 2012). In this method simulated annealing (SA) technique is adopted to find the best solution and it is compared with other intelligent optimization algorithms. Pathom Attaviriyanupap, *et al* (2005) formulated a bidding strategy for a day-ahead electricity market. In this paper optimal bidding parameters were determined by solving an optimization problem which includes the general constraints of Unit Commitment (UC). The problem becomes non-linear and non-differentiable which was difficult to solve by traditional optimization algorithm. So the author proposed a technique based on Evolutionary Programming to solve the problem. PSO is a natural searc (Yucekaya, *et al* 2009, Vijaya Kumar, J *et al* 2011) and is used to find an optimal solution for strategic bidding problems. But it takes much computational time to offer the best solution. To overcome this problem, a hybrid method such as Fuzzy-PSO (Bajpai P *et al* 2007) and SA-PSO (Soleymani S *et al* 2011) has been suggested to obtain the global best and optimal solution.

In this paper, the bidding strategy problem is modeled as an optimization problem and Firefly algorithm (FA) is used to solve the bidding strategy. A numerical example with six suppliers is used to illustrate the essential features of the proposed method. Comparative studies with conventional method have also been made to analyze the bidding coefficients, power, load, profit of Electricity Producers. The test results indicate that the proposed method improves the profit, converge much faster and more reliable than available methods..

2. Electricity Market structure and operations

An expressive market model describing the market mechanism and bidding procedure is constructed by considering several market elements and shown in Fig 1, which depicts a Restructured Electricity market

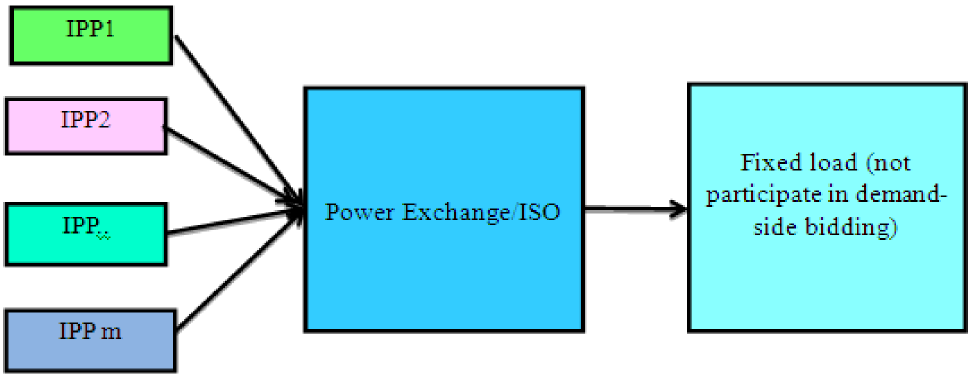

Fig. 2 Mathematical model of electricity market

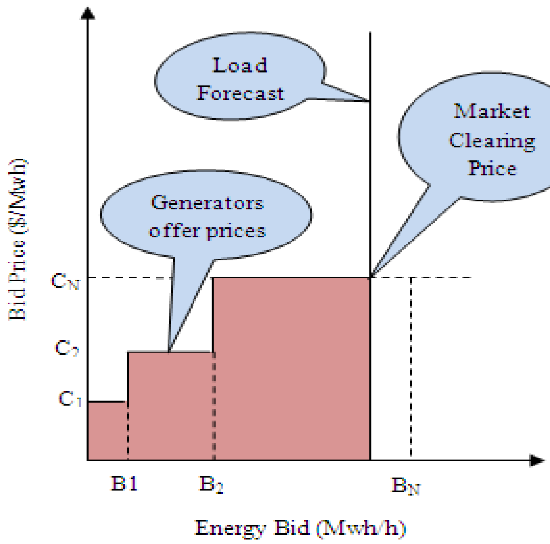

Fig. 3 Market equilibrium poit for MCP

(Mohammad Shahidehpour, *et al* 2000). Market mechanism is classified in to pool based model, bilateral contract model and hybrid model. A Pool based market structure is defined as a centralized market place that clears the market for buyers and sellers.

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. An ISO within a Pool based model 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. Power exchange (PX) accepts supply and demand bids to determine a MCP for each of the 24 periods in the trading day (Mohammad Shahidehpour, *et al* 2000). 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 lower bidding would lead to financial losses.

3. Electricity Market models

In order to achieve electricity market goals, several models for the market structure have been considered. Three basic models are outlined as follows (Mohammad Shahidehpour, *et al* 2000).

3.1 PoolCo model

A Pool Co is defined as a centralized marketplace that clears the market for buyers and sellers. 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

3.2 Bilateral Contracts Model

Bilateral contracts are negotiable agreements on delivery and receipt of power between two traders. These contracts set the terms and conditions of agreements independent of the ISO. However, in this model the ISO would verify that a sufficient transmission capacity exists to complete the

transactions and maintain the transmission security. The bilateral contract model is very flexible as trading parties specify their desired contract terms.

3.3 Hybrid Model

The hybrid model combines various features of the above two models. In the hybrid model, the utilization of a PoolCo is not obligatory, and any customer would be allowed to negotiate a power supply agreement directly with suppliers or choose to accept power at the spot market price. In this model, PoolCo would serve all participants (buyers and sellers) who choose not to sign bilateral contracts. The hybrid model is very costly setup because of separate entities required for operate to PX and transmission system

4. Problem formulation

4.1 Mathematical Model

The mathematical model of Pool based Electricity Market are presented in fig 2. Independent system operator (ISO) will receive bid from all market participants. Using predicted aggregate load from small users, ISO will determine MCP that will balance the energy demand and Supply. This process is graphically expressed in fig 3.

The objective of IPPs 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:

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

Market Clearing Price (R) represented by the following equation

$$R = \frac{Q_0 + \sum_{i=1}^{m} \frac{a_i}{b_i}}{K + \sum_{i=1}^{m} \frac{1}{b_i}} \tag{3}$$

The aggregated load demand formulated as follows

$$Q(R) = Q_o - KR \tag{4}$$

Constraints

1. Power balance constraints:

$$\sum_{i=1}^{m} P_i = Q(R) \tag{5}$$

$$p_i = \frac{R - a_i}{b_i} \qquad i = 1,2.....m \tag{6}$$

2. Power generation limit constraints:

$$p_{i\min} \le p_i \le p_{i\max} \qquad i = 1,2......n \tag{7}$$

Where

$F(a_i, b_i)$ Profit of i^{th} electricity producer
$C_i(P_i)$ Cost function of i^{th} electricity producer
P_i Output power of i^{th} electricity producer
$Q(R)$ 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*.
M No of generating units

4.2 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 for the analysis. The i^{th} GENCO can determine mean and standard deviations of bidding coefficients based on their historical data. Normally the data of bidding coefficients are random variables with the following probability density function (pdf).

$$pdf(x_i) = \frac{1}{\sqrt{2\pi\sigma_i}} \exp\left(-\frac{(x_i - \mu_i)^2}{2\sigma_i^2}\right) \tag{8}$$

Where,
σ_i - Standard deviation
μ_i - Mean values

When the problem is looked from the p^{th} *(p=1,2,……,n+m)* participant, the bidding coefficients of the j^{th} *(j=1,2,…..,n and j≠p)* supplier, a_j and b_j ,follows a joint normal distribution with the following probability density function (pdf).

$$pdf(a_i, b_i) = \frac{1}{2\Pi\sigma_j^{(a)}\sigma_j^{(b)}\sqrt{1-\rho_j^2}} \times \exp\left\{-\frac{1}{2(1-\rho_j^2)}\left[\left(\frac{a_j - \mu_j^{(a)}}{\sigma_j^{(a)}}\right)^2 - \frac{2\rho_j(a_j - \mu_j^{(a)})(b_j - \mu_j^{(b)})}{\sigma_j^{(a)}\sigma_j^{(b)}} + \left(\frac{b_j - b_j^{(b)}}{\sigma_j^{(b)}}\right)^2\right]\right\} \tag{9}$$

Where ρ_j is the correlation co-efficient between a_j and b_j

The mean $\mu_j^{(a)}, \mu_j^{(b)}$ and standard deviation $\sigma_j^{(a)}$, $\sigma_j^{(b)}$ are the parameter of the joint distribution. The marginal distribution of a_j, b_j are normal with mean values $\mu_j^{(a)}$, $\mu_j^{(b)}$ and standard deviations $\sigma_j^{(a)}$, $\sigma_j^{(b)}$ respectively. Based on historical bidding data these distributions can be determined. Using probability density function (13) for suppliers as well as large consumers the joint distribution between a_j, b_j and between c_j, d_j the optimal bidding problem with objective functions given in equation (2) and constraints (5) to (7) becomes a stochastic optimization problem.

4.3 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

$$F(a,b) = (1-\lambda)E(F) - \lambda D(F) \tag{10}$$

Subject to

$$P_{i\min} \leq \frac{(E(R)-a_i)}{b_i} \leq / P_{i\max} \tag{11}$$

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 Firefly algorithm.

5. Proposed methodology

5.1. Overview of Firefly algorithm

The firefly algorithm (FA) is a metaheuristic, nature inspired, optimization algorithm which is based on the social flashing behavior of fireflies, or lighting bugs, in the summer sky in the tropical temperature regions (-3, 20). It was developed by Dr. Xin-she yang at Cambridge University in 2007, and it is based on the swarm behavior such as fish, insects, or bird schooling in nature (Xin-She Yang, *et al* 2012) & (Chandrasekaran, K *et al* 2012). In particular, although the firefly algorithm has many similarities with other algorithms which are based on the so-called swarm intelligence, such as the famous Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC) optimization, and bacterial foraging algorithms (BFA), it is indeed much simpler both in concept and implementation. According to recent bibliography, the algorithm is very efficient and can outperform other conventional algorithms, such as Genetic algorithms, for solving many optimization problems; a fact that has been justified in a recent research, where the statistical performance of the firefly algorithms was measured against other well known optimization algorithm using various standard stochastic test functions. Its main advantage is the fact that it uses mainly real random numbers, and it is based on the global communication among the swarming particles (fireflies) and as a result, it seems more effective in optimization such as the optimal bidding problem in our case.

5.2. Characteristics of firefly algorithm

The Firefly algorithm has three particular idealized rules which are based on some of the major flashing characteristics of the real fireflies.

(i) All fireflies are unisex, and they will move towards more attractive and brighter ones regardless of their sex.

(ii) The degree of attractiveness of a Firefly is proportional to its brightness which decreases as the distance from the other firefly increases due to the fact that the air absorbs light. If there is no brighter one than a particular firefly, it will move randomly.

(iii) The brightness or light intensity of a firefly is determined by the value of the objective function of a given problem. For maximization problems, the light intensity is proportional to the value of the objective function.

5.3 Functions of firefly algorithm

5.3.1. Attractiveness

The form of attractiveness function of a firefly is the following monotonically decreasing function: Where, r is the distance between any two fireflies, β_0 is the initial attractiveness at r =0, and γ is an absorption coefficient which controls the decrease of the light intensity.

$$\beta(r) = \beta_0 \exp(\gamma r^m) \quad \text{With } m \geq 1 \tag{12}$$

5.3.2. Distance

The distance between any two fireflies i and j, at positions x_i and x_j respectively, can be defined as a Cartesian Euclidean distance as follows:

$$R_{ij} = \left|x_i - x_j\right| = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \tag{13}$$

Where $x_{i,k}$ is the k^{th} component of the spatial coordinate x_i of the i^{th} firefly and d is the number of dimensions. In 2D case we have

$$R_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{14}$$

However, the calculation of distance R can also be defined using other distance metrics, based on the nature of the problem, such as Manhattan distance or mahalanobis distance.

5.3.3. Movement

The movement of the Firefly *i* which is attracted by a more attractive (i.e. brighter) firefly *j* is given by the following equation:

$$x_i^{t+1} = x_i^{t} + \beta_0 \exp(-\gamma\, r^2_{ij})\,(x_j - x_i) + a\left(rand - \frac{1}{2}\right) \tag{15}$$

Where the first term is the current position of a Firefly, the second term is used for considering a firefly's attractiveness to light intensity seen by adjacent fireflies and the third term is used for random movement of a firefly when the brighter ones are not available. The coefficient a is a randomization parameter determined by the problem of interest, while rand is a random number generator uniformly distributed in the space which is (0,1).

5.4 Convergence and Asymptotic Behavior

The convergence of the algorithm is achieved for any large number of fireflies (n) if $n >> m$, where m is the number of local optima of an optimization problem .In this case initial location of *n* firefly is distributed uniformly in the entire search space. The algorithm will approach global optima when n$\rightarrow$ ∞ and t >> 1. The appropriate choice of the number of iteration together with the α, β, γ and *n* parameter highly depend on the nature of the given optimization problem as this affect the convergence of the algorithm.

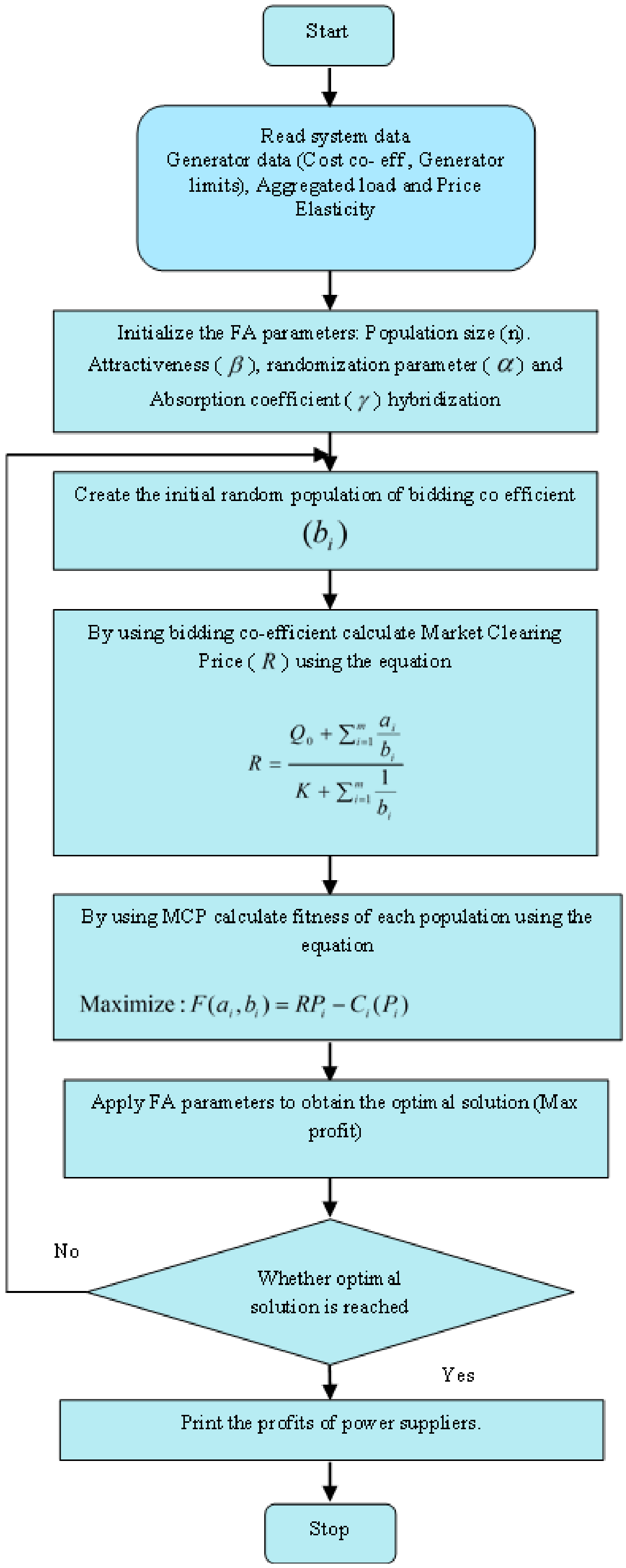

Fig.4 Flow chart for proposed method

5.5 Implementation of Firefly algorithm to solve bidding problem

In order to sell electricity at optimal prices and to maximize profit, power producers and consumers need exclusive bidding strategies that must consider constraints such as Power balance, Generator limits and Load consumption limits of market participants. So it is recommended that the Firefly Algorithm can directly solve optimal bidding problem (Maximize profit) because it is a maximization optimizing algorithm. The flow chart of proposed method is shown in fig. 4. Firefly Algorithm has four essential parameters Population size (n), Attractiveness (β), randomization parameter (α) and Absorption coefficient (γ).The feasible parameters obtained by iterative processes are as follows. α = 0.2 – 0.9, β = 0.2 – 1.0, γ = 0.1 – 10 and n = 25 – 50. Therefore, the following parameters of the proposed FA are considered to solve the optimal bidding problem of six independent power producers and two large consumers. Where n = 30, $\beta = 0.20$, $\alpha = 0.25$, $\gamma = 1$ and maximum number of iterations = 5000. Owing to the random nature of the FA, their performance cannot be judged by the result of a single run. Many trials with independent population initializations should be made to obtain a useful conclusion of the performance of the approach. To demonstrate the superiority of the proposed FA, the test results are also compared with the results already reported by the most recently published methods such as PSO, GA and Monte Carlo method for solving the bidding problem. All scenarios are programmed in MATLAB 9.0 and simulation is carried on a computer with a Pentium IV, Intel Dual core 2.2 GHz, 2 GB RAM.

5. Case study and results

The proposed Firefly approach has been applied to a test system given in reference (Ma, X *et al* 2005) which consists of six Independent power Producers (IPPs).

Table 1 Data of Independent power Producers

IPPs	e ($/h)	f ($/MWh)	P_{imin} (MW)	P_{imax} (MW)
1	2.0	0.00875	50	160
2	1.75	0.035	50	100
3	1.0	0.0625	30	80
4	3.15	0.00334	30	80
5	3.0	0.015	10	60
6	3.0	0.015	10	60

Table 2 Simulation results for independent Power producers

IPPs	Bidding Strategy ($/MW)	Bidding Power(MW)	MCP	Profit ($)
1	0.0138	158.6641		238.9235
2	0.049	50		78.75
3	0.0837	31.2829	4.1	76.6493
4	0.0147	71.3485		66.4166
5	0.0463	25.8886		26.0396
6	0.0463	25.8886		26.0376

The cost coefficients of power generation and maximum/ minimum limits of six Independent power Producers given in Table 1. The fuel cost function of each generator is estimated as quadratic equation. The parameters associated with the load characteristics are considered from the same reference where in aggravated load Q_0 is equals to 450 MW and price elasticity K equals to 20. The simulation results of Independent power Producers presented in Table 2.

Table 3 Comparison of market clearing price and power of Power suppliers

IPPs	Firefly (Proposed)		Conventional method	
	MCP	P(MW)	MCP	P(MW)
1		158.6641		156.01
2		50.0000		61.78
3	4.1000	31.2829	4.0386	37.95
4		71.3485		64.84
5		25.8886		24.47
6		25.8886		24.47

Comparative studies with conventional method have also been made to analyze the MCP and bidding power of IPPs and are displayed in Table 3. Sometimes, there may be a chance to the suppliers to receive erroneous market information. At that time, the variation of profit of the supplier is analyzed by changing the value of risk factor (λ), using the equation (10) subjected to constraint (11). The simulation results of the second supplier for various value of λ and corresponding change in profit against risk factor are shown in Table 4.

Table 4 Profit of IPPs by considering risk

S.No	%of risk	Profit ($)
1	0	78.75
2	0.2	65.038
3	0.4	61.682
4	0.6	57.728
5	0.8	53.428
6	0.9	51.613

From the results, it is clear that the proposed method provides maximum profits compared to conventional method. Also, it converges much faster and more reliable than the other available methods.

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Biography of Authors

K. Asokan received the B.E degree in Electrical and Electronics Engineering and the M.E degree in Power Systems with distinction from Annamalai University, Annamalainagar, India in the year 2001 and 2008 respectively. He is currently pursuing his research program in the Department of Electrical Engineering and working as a Assistant Professor in the same department. His research interests include power system operation and control, Deregulated power systems and computational intelligence applications

R. Ashok Kumar is presently the Professor of Electrical Engineering, Annamalai University, India .His research interest includes Power system operation and control, Design analysis of Electrical Machines, Radial distributed system and deregulated power system studies. He has published many reports and journal articles in his research area. He received M.E degree (Power System Engineering) in 1999 and Ph.D degree in 2009 both from Annamalai University. In 1994 he joined Annamalai University as a Lecturer then elevated to the level of Professor. He is a member of ISTE and other technical bodies