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Optimal Bidding Strategy in Competitive Market Using GA & BFA: A Comparative Study

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Abstract—The electricity markets have been restructured to improve the efficiency. Bidding by gencos is one such challenge. Because of competition gencos are devoid of information about their competitors while developing their respective bids. Bacterial foraging algorithm is proposed to determine the optimal bidding strategy in competitive auction market. The market includes generating companies (Gencos), large consumers who participate in demand side bidding, and small consumers whose demand is present in aggregate form. By using previous bidding data and multi-round auction process, the optimal bidding strategy for both Gencos and large consumers is obtained. Programming has been carried out, to obtain bidding strategies under different ways of modeling the competitors. The bidding method have been extended to study the effect of contract on bidding. Test results show that Bacterial foraging algorithm gives better profits than genetic algorithm..

Keywords—Power Exchange (PX), Optimal Power Flow (OPF), independent system operator (ISO), Genetic algorithm (GA), Bacterial foraging algorithm(BFA),Independent Power Producer(IPP).

I. INTRODUCTION

To tackle several complex search problems of real world, scientists have been looking into the nature for years - both as model and as metaphor - for inspiration. Optimization is at the heart of many natural processes like Darwinian evolution, group behaviour of social insects and the foraging strategy of other microbial creatures. Natural selection tends to eliminate species with poor foraging strategies and favour the propagation of genes of species with successful foraging behaviour, as they are more likely to enjoy reproductive success.

Since a foraging organism or animal takes necessary action to maximize the energy utilized per unit time spent for foraging, considering all the constraints presented by its own physiology such as sensing and cognitive capabilities, environment (e.g. density of prey, risks from predators, physical characteristics of the search space), the natural foraging strategy can lead to optimization and essentially this idea can be applied to real-world optimization problems.

Based on this conception, Passino proposed an optimization technique known as Bacterial Foraging Optimization Algorithm (BFOA) [1, 2]. Until date, the algorithm has successfully been applied to real world problems like optimal controller design [1 - 3], harmonic estimation [4], transmission loss reduction [5], pattern recognition [6] and design of active power filters [7].

One of the major steps in BFOA is the event of reproduction in which the bacterial population is at first sorted in order of ascending accumulated cost (value of the objective function to be optimized), then the worse half of the population containing least healthy bacteria is liquidated while all the members of the better half is split into two bacteria which are placed in the same location. As pointed out by Passino, this phenomenon finds analogy with the selection mechanism incorporated in classical evolutionary algorithms (EA) [1, 2, and 8]. Bacteria in the most favourable environment (i.e., near an optima gain a selective advantage for reproduction through the cumulative cost).

A first step towards the mathematical analysis of the chemo taxis operation in BFOA has recently been taken by Dasgupta et al. [9]. This article following the same train of thoughts appears as one approach for mathematical analysis of the reproduction mechanism in BFOA.

Deregulation has paved the ways for private players to emerge and also it brings competitiveness among the existing companies. We can see that the regulated structure of power system was not efficient. For developing countries, the main issues are high demand growth coupled with inefficient system management and irrational tariff policies. This has affected the availability of financial resources to support investments. The electricity bill for the end consumer now involves at least two components: one from the distribution and transmission network-operator responsible for the network and services, and the other from the company that generates the electrical energy[10].

A. Regulation:

The Government has set down laws and rules that put limits on and define how a particular industry or company can operate. Regulation of electric utilities is not the only way government can control the electric power industry within its jurisdiction.

B. Deregulation:

Deregulation in power industry is a restructuring of the rules and economic incentives that governments set up to control and drive the electric power industry. A system operator is appointed for the whole system and it is entrusted with the responsibility of keeping the system in balance, i.e. to ensure that the production and imports continuously match consumption and exports. This system operator is known as Independent System Operator (ISO)[11].

The electricity price gets segregated into the following:

- Price of electrical energy
- Price of energy delivery (wheeling charges)
- Price of other services

C. Power Market:
There must be some way for power producers to sell their power, and for buyers to buy the power.

D. System Operation:
The transmission system can move power from seller's site to the buyer's locations, but it must be kept under proper control on a real time basis.

There are three basic ways in which it can be done: Poolco, Bilateral Trading and Power Exchange. Often these are combined in different ways to form a composite mechanism.

a. Poolco

There is only one buyer in this system. The Poolco is a governmental or quasi-governmental agency that buys for everyone, taking bids from all sellers and buying enough power to meet the total need, taking the lowest cost bidders. The Poolco operator also has responsibility for running the power system, and is thus a combined buyer-system operator.

b. Bilateral Exchange

In this type of multi-seller/ multi-buyer system, individual buyers and sellers make a deal to exchange a power at prices and under this condition they agree to, privately.

c. Power Exchange (PX)

The Government sets up, or causes the power industry to establish, a trading exchange for electric power, which operates much like a stock exchange. The buyers and sellers enter their needs into the power exchange.

These three market mechanisms are not mutually exclusive. Multiple combinations of all three could be made to work.

Major responsibilities of Independent System Operator:
The ISO (or PX) sets the market spot price based on the last generator dispatched in order to balance the Power market's generation and demand.

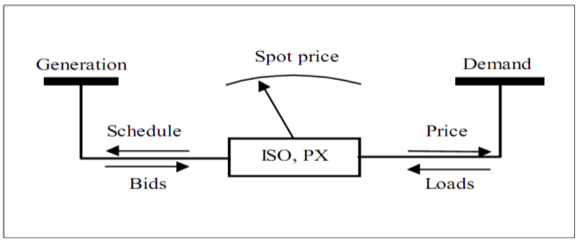

Fig. 1 Power market

The ISO has following basic functions laid out for it[12]:
System security: Operator must assure that the power system continues to operate in a stable, economical manner.
Power Delivery: The operator should provide the power transportation services requested of it by buyers and sellers.
Transmission pricing: System operator must determine and post the prices for transmission usage, offer to reserve or sell usage, track, bill and settle with users, and pass on revenues to transmission owners.
Service quality assurance: The system operator must assure the quality of service it provides.
Promotion of Economic efficiency and equity: The overall operations of system operator should obey economic efficiency and also it should have fairness and equity in its dealing and should not benefit only some players in the system.
There are three different ways mainly adopted to tackle the network congestion:

- Price Area Congestion Management
- Available Transfer Capability (ATC) based Congestion Management
- Optimal Power Flow (OPF) based Congestion Management.

The methods by which the optimal bidding problem is solved are as follows [13]:

- Game theory.
- Dynamic Programming.
- A genetic algorithm based method.
- Optimization based bidding strategies.
- Markov Decision Process.

II. MARKET STRUCTURE AND OPERATION

A. Game theory:

Game theory has been extensively used in microeconomic analysis, where its prediction record has been remarkable in areas such as industrial organization theory. Game theory is the mathematical theory of bargaining [13].

B. Objectives of market operation:

There are two objectives for establishing an electricity market ensuring a secure operation and Facilitating an economical operation.

C. ISO (independent system operator):

The ISO administers transmission tariffs, maintains the system security, coordinates maintenance scheduling, and has a role in coordinating long-term planning.

D. Electricity market models:

- Poolco model
- Bilateral contracts model
- Hybrid model

III. OPTIMAL BIDDING STRATEGY

Power system deregulation is designed to allow competition among market participants, leading to a higher efficiency. In general, oligopoly market model is used to represent the competitive electricity market behavior, which is dominated by large sellers whose decisions affect the market price. For inelastic demand, dominant sellers can use a strategy to raise their supply curve and increase the market price to gain a higher profit. This ability is called market power. The objective of the firms in oligopoly market is to maximize its own profit and this lead to the optimal bidding strategy problem. There are many ways to find the optimal bidding strategy. The average of bidding parameter was calculated to be the optimal strategy. In, genetic algorithm (GA) was used to find the optimal bidding strategy in the auction market. For this work, encoded price that defines a price that buyer or seller should offer in next round of bidding is created. GA develops this encoded bidding price through crossover and mutation process. The profit of all participants must be known to find fitness value and calculate the price. This fitness function is the weakness of this algorithm because each firm cannot know other profits. In this paper, bacterial foraging algorithm is used to find the optimal bidding strategy based on historical bidding data and multi-round auction mechanism. Structure of market is presented while algorithm for BFA and auction market is presented. Result of the proposed algorithm is compared with Monte Carlo Simulation technique, genetic algorithm.

A. Market structure:

Market structure used consists of m number of sellers or IPP and n number of large consumer. These two groups of market participant submit linear demand and supply curves to Power Exchange (PX) and try to maximize its profit by developing an adaptive strategy. This market also includes aggregated load model for small consumers whose consumption is not varied by market price.

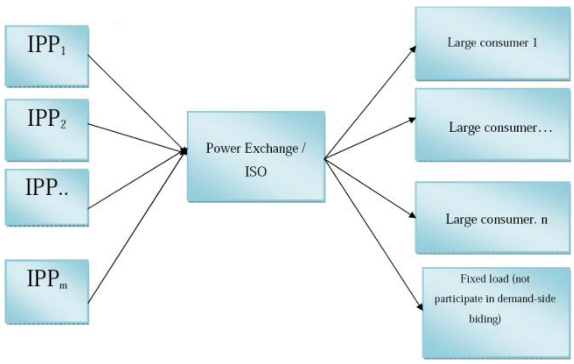

Fig. 2 Market Structure

Let m Independent Power Producers (IPPs) bid linear supply curve denoted by $R= a_i+P_ib_i$ when i=1, 2,…, m and n large consumers bid linear demand curve denoted by $R=c_j-d_jL_j$ 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 aggregate load is represented by $Q=Q_0-KR$ when K is the price elasticity of small customer.

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

$Ci(Pi) =e_ip_i+f_iP_i$

And market use uniform pricing scheme. The objective of power producer can be defined as:

$\text{Max } F_i\ (a_i\ ,\ b_i\ )=RP_i - C_i\ (P_i)$ (1)

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

$B_j(L_j)=g_jL_j-h_jL_j^2$.

The objective of large consumer can be defined as:
Max F_i (c_j , d_j)= $B_j(L_j)$–RL_j (2)
Subject to power balance constraint neglecting loss:

$$\sum_{i=1}^{m} P_m = Q + \sum_{j=1}^{n} L_j \qquad (3)$$

where

$$P_i = \frac{R - a_i}{b_i} \quad \text{for supply curve} \qquad (4)$$

$$L_j = \frac{C_j - R}{d_j} \quad \text{for demand curve} \qquad (5)$$

Power generation and consumption limit constraints
$P_{min,i} \le P_i \le P_{max,i}$ (6)

$L_{min,j} \le L_j \le L_{max,j}$ *(7)*

$$R = \frac{\sum_{i=1}^{m}(\frac{a_i}{b_i}) + \sum_{j=1}^{n}(\frac{c_j}{d_j})}{K + \sum_{i=1}^{m}(\frac{1}{b_i}) + \sum_{j=1}^{n}(\frac{1}{d_j})} \qquad (8)$$

Market clearing price (MCP) is determined from (3), (4) and (5). Using R from (8) in (4) and (5), if Pi or Lj is below its limit, remove that generator or consumer from the system and calculate R again. Similarly, if Pi or Lj is greater than its limit, set Pi or Lj at its upper limit and calculate R again by ignoring that generator or consumer since it is no longer a marginal unit. Continue this process until all power produced and consumed by each firm is within the limit, MCP is finally obtained. It is clear that market participants can set MCP at the level that returns the maximum profit to them if they know bidding strategy of other firms. But in sealed bid auction based electricity market, information for the next bidding period is confidential in which IPPs and large consumers cannot solve optimization problem (1) and (2) directly. However, bidding information of previous round will be disclosed after ISO decide MCP and everyone can make use of this information to strategically bid for the next round of auction.

B. Problem formulation

The optimal bidding problem is defined as maximizing the profit of every committed generators
and loads
n-total no of plants.
Pi Generation / Load of 'i'th plant.

$$F_i = R * P_i - (e_i P_i + f_i P^2{}_i)$$

Where $K * R = Q_0 - \sum_{i=1}^{n} P_i$

The total profit of all plants is to be maximized so the problem is defined like this maximize

$$F = R * \sum_{i=1}^{n} P_i - \sum_{i=1}^{n}(e_i P_i + f_i P_i{}^2)$$

Subject to the constraints

$$Q_0 - \sum_{i=1}^{n} P_i - k * R = 0$$

and the limits.
For generators $P_i^{min} \le P_i \le P_i^{max}$
For loads $-P_i^{max} \le P_i \le P_i^{min}$.

Minimize

$$-F = -R*\sum_{i=1}^{n} P_i + \sum_{i=1}^{n}(e_i P_i^2 + f_i P_i)$$

Subject to the constraints

$$Q_0 - \sum_{i=1}^{n} P_i - K*R = 0$$

And the limits

For generator $P_i^{min} \leq P_i \leq P_i^{max}$

For loads $-P_i^{max} \leq P_i \leq -P_i^{min}$

C. Auction market:

Auction is an important mechanism to make a transaction between suppliers and Consumers. With the proposed algorithm, market is efficient because the valuation of electric is widely known. In fact, the valuation may be known from trade paper, daily newspaper or online communication service. Players will consider their status whether current profit is acceptable or not. If any players deem that they can gain more profit, they can make a new round of auction.

The optimal bidding strategy is satisfied by allowing players to adjust their bid if they believe they can make more profit in the next round of bid.

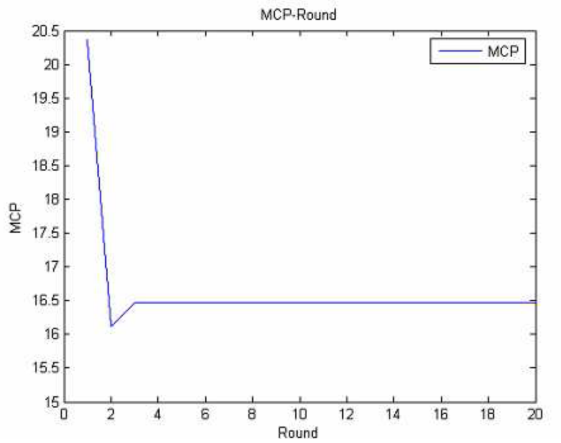

Fig. 3 change of MCP during auction process

The change in market clearing price each round of bidding is shown in Fig Market price is fluctuated around equilibrium price before converging.

IV. GENETIC ALGORITHM BASED BIDDING STRATEGY

Each and every point in the search space corresponds to one set of values for the parameters of the problem. Each parameter is code with a string of bits. The individual bit is called 'gene' .The total string of such genes of all parameters written in a sequence is called a 'chromosome'. So, there exists a chromosome for each point in the search space. The set of search points selected and used for processing is called a 'population', i.e., population is a set of chromosomes. The number of chromosomes in a population is called 'population size' and the total number of genes in a string is called 'string length'.

Each population member is then evaluated for the given objective function is assigned fitness. The algorithm then checks for the stopping condition. The condition can be either all population members assume equal fitness values or when a maximum number of generations are reached. If the condition is not satisfied, the population members are arranged in descending order of their fitness value and genetic operators are applied to produce new and better fit population from old population while applying genetic operators like recombination, elitism, crossover and mutation. This completes one iteration and in GA terminology one generation. The generation count is updated and the process is repeated.

A. Genetic algorithm (GA):

1. [Start] Generate random population of n chromosomes
2. [Fitness] Evaluate the fitness f(x) of each chromosome x in the population
3. [New population] Create a new population by repeating following steps until the new population is complete

3.1. [Selection] Select two parent chromosomes from a population according to their fitness (the bigger fitness, the higher chance to be selected)

3.2. [Crossover] with a crossover probability, crossover parents to form new offspring (children). If no crossover is performed, offspring is the exact copy of parents.

3.3. [Mutation] with a mutation probability, mutate new offspring at each locus (position in chromosome).

3.4. [Accepting] Place new offspring in the new population

4. [Replace] Use new generated population for a further run of the algorithm

5. [Test] if the end condition is satisfied, stop, and return the best solution in current population.
6. [Loop] Go to step 2

In this paper, genetic algorithm is applied by using MATLAB developed by Math Works,. For this application, it need proper input objective function to find optimal solution when the parameter such as size of population, number of generation, crossover fraction, etc. Auction is an important mechanism to make a transaction between suppliers and consumers. With the proposed algorithm, market is efficient because the valuation of electric is widely known. In fact, the valuation may be known from trade paper, daily newspaper or online communication service. Players will consider their status whether current profit is acceptable or not. If any players deem that they can gain more profit, they can make a new round of auction. This process will continue until nobody wants to change their bids. Typically it consist of three phases,

a. Generation
b. Evaluation
c. Genetic operation

a. Generation:
In this number of chromosomes equal to population size is generated and each is of length equals to string length. The size of population is direct indication of effective representation of whole search space in one population.

b. Evaluation
In this phase, suitability of each of the solutions from the initial set as the solution of the optimization problem is determined. For this function called "fitness function" is defined.

c. Genetic operation
In this phase, the objective is the generation of new population from the existing population with the examination of fitness values of chromosomes and application of genetic operators. These genetic operators are reproduction, crossover, and mutation. This phase is carried out if we are not satisfied with the solution obtained earlier.

B. Parameters used in Genetic algorithm
Population size=30
Chromosome length=16
Elitism probability=0.2
Crossover probability=0.6
Mutation probability=0.05
Number of generations=1000

Table I: **Comparison of Generated Power**

Bus number	Generated power calculated using Monte Carlo simulation(MW)[10]	Generated power calculated using genetic algorithm(MW)
1	160	160
2	89.4	100.435
3	45.7	45.166
4	88.8	120
5	43.1	49.4714
6	43.1	49.4714
7	-139.7	-125.991
8	-112.1	-98.54

Table III: **Comparison of Benefits**

Bus number	Benefit calculated using monto-carlo simulation($)[10]	Benefit calculated using GA($)
1	1368	1617
2	572.7	741.4
3	322.9	392.7
4	386.4	614
5	177.5	257
6	177.5	257
7	-1126	-888.9
8	-592.6	-407.9

Table IIIII: **Comparison of bidding values**

Bus number	Bidding values Obtained using Monte Carlo simulation[10]	Bidding values Obtained using Genetic Algorithm
1	0.02927	0.027207
2	0.12420	0.126932
3	0.29231	0.332454
4	0.07433	0.06041
5	0.17058	0.18091
6	0.17058	0.18091
7	0.09771	0.096981
8	0.07719	0.072736

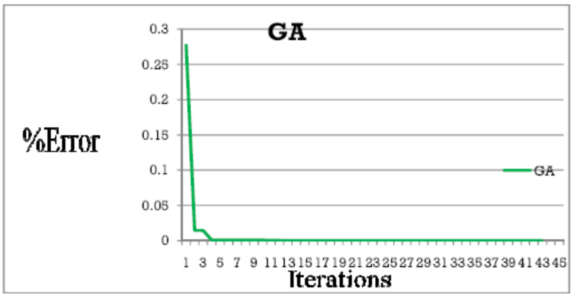

Fig. 4 convergence of Genetic Algorithm

The GA gives better benefits when compared to Monte Carlo simulation [1] and optimal values of lambda using GA are more when compared to Monte Carlo simulation.

V. BACTERIAL FORAGING ALGORITHM BASED BIDDING STRATEGY

Bacterial Optimization Algorithm (BFOA) based on the bacterial strategies of the E. Coli bacterium cells. Natural selection tends to eliminate animals with poor bacterial strategies (methods for locating, handling, and ingesting food) and favor the propagation of genes of those animals that have successful bacterial strategies, since they are more likely to enjoy reproductive success (they obtain enough food to enable them to reproduce). After many generations, poor bacterial strategies are either eliminated or shaped into good ones (redesigned). Logically, such evolutionary principles have led scientists in the field of bacterial theory to hypothesize that it is appropriate to model the activity of bacterial as an optimization process: a bacterial animal takes actions to maximize the energy obtained per unit time spent bacterial, in the face of constraints presented by its own physiology and environment.

Bacterial can be modeled as an optimization process where an animal seeks to maximize the energy obtained per unit time spent bacterial. We begin by overviewing the relevant research in bacterial theory, bacterial by communicating organisms (social bacterial) which sometimes operate in swarms, and the relevance of these areas to optimization.

A. BFO operation

The bacterial behavior of E. coli (bacterial present in our intestines) can be explained by four processes namely, chemo taxis, swarming, reproduction, and elimination and dispersal as presented below.

B. Chemo taxis

The locomotion is achieved by a set of rigid flagella which enable the bacterial to swim. This left-handed helix configured flagellum either rotates counter clockwise to create the force against bacterium to push the cell or rotates in clockwise direction to pull at the cell. This mechanism of creating rotational forces to spin the flagellum in either direction is named as biological motor.

An E. coli bacterium can move in two different ways, it can swim or it can tumble. The bacterium moves in a specified direction during and during tumbling it does not have a set direction of movement and there is little displacement. Generally, the bacterium alternates between these two modes of operation in its entire lifetime. This alternation between the two modes enables the bacterial to move in random directions and search for nutrients.

$$\theta^t(j+1,k,l) = \theta^t(j,k,l) + C(i) * \frac{\Delta(i)}{\sqrt{\Delta(i) * \Delta(i)}}$$

Δ(i)=Random vector
Δ(i)=Transpose of vectorΔ(i)
$C(i)$=step size

C. Swarming

When any one of the bacterial reaches the better location, it should attract other bacterial so that they converge in that location .In order to meet these criteria, the E. coli cells provide an attraction signal to each other so that they swarm together. The swarming pattern seems form based on dominance of the two stimuli (cell-to-cell signaling and bacterial). This can be achieved by a cost function adjustment based upon the relative distances of each bacterium from the fittest bacterium. When all the bacterial have merged into the solution point this adjustment is no more to be performed. The effect of swarming is to make the bacterial congregate into groups and move as concentric patterns with high bacterial density.

$$J_{cc}(\theta^i(j,k,l),P(j,k,l)) = \sum_{i=1}^{s} J_{cc}{}^{i}(\theta^i(j,k,l),P(j,k,l))$$

$$= \sum_{i=1}^{s} -d_{attractive}\exp(-W_{attract})\sum_{m=1}^{p}(\theta^m-\theta_i{}^m)^2 + \sum_{i=1}^{s} -h_{repelent}\exp(-W_{repelent})\sum_{m=1}^{p}(\theta^m-\theta_i{}^m)^2$$

J_{cc} =the relative distances of each bacterium from the fittest bacterium
S =number of bacterial
P =number of parameters to be optimized
θ^i =position of the fittest bacterial
d attract , *w attract* , *h repelent* , *w repelent* =different parameters

D. Reproduction

After the end of chemo taxis event the final population of bacterial undergoes the reproduction stage, where the least healthy bacterial die and the other healthiest bacterial split into two at the same location thus ensuring that the population of the bacterial remains constant.

E. Elimination and dispersal

A gradual or sudden change in the location may occur due to consumption of nutrients or some other influence. This may cause the elimination of a set of bacterial and/or disperse them to a new environment. This reduces the chances of convergence at local optima location.

The algorithm

Step 1**:** Initialization
(a) Number of bacterial (S), number of parameters (p) to be optimized.
(b) Swimming length (Ns) is the maximum number of steps taken by each bacterium when it
moves from low nutrient area to high nutrient area, N_c is the number of chemotactic steps taken by each bacterium before reproduction ($N_c > N_s$), Nre and Ned are the number of reproduction and elimination–dispersal events.
(c) Ped is the probability of elimination and dispersal.
(d) Specifying the location of the initial position of bacterial by random numbers on [0, 1].
(e) The values of dattract, xattract, hrepellent and xrepellent.
(f) Random swim direction vector D(i) and run length vector C(i)=[C(1);C(2;)….C(p)] where C(1);C(2;)….C(p) are the run length vector corresponding to the each parameter,
Respectively.
Step 2: Iterative algorithm for optimization This explains the main part of the algorithm, i.e., evaluation of chemotaxis, swarming, reproduction, elimination and dispersal process. It starts with the calculation of J error for the initial bacterial population inside the innermost chemotaxis loop. Any ith bacterial at the jth chemotactic, kth reproduction and lth elimination stage is represented by q (*j*, *k*, *l*) and its corresponding error value is given by J error (i, j,k, l) (initially, j = k = l = 0).
The algorithm works as follows
(1) Starting of the elimination–dispersal loop (l =l+1)
(2) Starting of the reproduction loop (k = k + 1)
(3) Starting of the chemotaxis loop (j = j + 1)
(a) For all i =1; 2; . . . ; S, calculate J error (i, j,k, l)
(b) J error (i, j,k, l) is saved as J errorold so as to compare with other J error values.
(c) Tumble: Generate a random vector D(i) e Rp with each element being a random number in the range [_1, 1].
(d) Move:

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + c(i)\frac{\Delta(i)}{\sqrt{\Delta(i)'*\Delta(i)}}$$

This results in a step size C(i) in the direction of the tumble for i^{th} bacterium.
(e) Calculate J error (i, j+1, k, l)
(f) Swimming loop:
Let m = 0 (counter for swim length)
While m < NS
m = m + 1;
If J error (i, j + 1,k, l) < $J_{errorold}$, then $J_{errorold}$ = J error(i, j + 1,k, l) and

$\theta^{i}(j+1,k,l)=\theta^{t}(j+1,k,l)+c(i)\frac{\Delta(i)}{\sqrt{\Delta(i)'*\Delta(i)}}$ This θ^{i} (j+1,k,l) is then used to calculated new J error (i,j+1,k,l).
Else m=NS.
(g) Go to the next bacterium (i + 1) till all the bacterial undergo chemotaxis.
(4) Reproduction:
(a) For the given k and l, and for each i =1; 2; . . . S, let *i*

$$J^{i}{}_{healyh}=\sum_{J=1}^{N_c+1}J_{error}(i,j,k,l)$$

be the health of i_{th} bacterium. The bacterial are sorted according to ascending order of J_{health}.
(b) The bacterial with the highest J_{health} values die and those with minimum values split and the copies that are made already, now placed at the same location as their parent.
(5) If k < Nre go to step 3 to start the next generation in the chemotactic loop else go to step 7.
(6) Elimination–dispersal: For i =1; 2 . . . S, a random number is generated and if it is less than or equal to Ped, then that bacterium is dispersed to a new random location else it remains at its original location.
(7) If l < Ned go to step 2 else stop.

For 30 bus system:

Table IV: **Comparison of bidding parameters**

Bus number	**Bidding values obtained using Montecarlo simulation[1]**	**Bidding values obtained using Genetic Algorithm**	**Bidding values obtained using Bacterial Foraging Algorithm**
1	0.02927	0.027207	0.0270
2	0.12420	0.126932	0.126
3	0.29231	0.332454	0.332
4	0.07433	0.06041	0.061
5	0.17058	0.18091	0.180
6	0.17058	0.18091	0.180
7	0.09771	0.096981	0.090
8	0.07719	0.072736	0.072

Table V: **Comparison of bidding parameters**

Bus Number	**Generated power Calculated using Monte carlo simulation (MW)[1]**	**Generated power calculated using genetic algorithm (MW)**	**Generated power calculated using bacterial foraging algorithm (MW)**
1	160	160	160
2	89.4	100.435	99.83
3	45.7	45.166	44.8
4	88.8	120	120
5	43.1	49.4714	49.22
6	43.1	49.4714	49.22
7	-139.7	-125.991	-125.104
8	-112.1	-98.54	-97.9

Table VI: **Comparison of Benefits**

Bus Number	**Benefits calculated using monte carlo simulation($)**	**Benefits calculated using genetic algorithm($)**	**Benefits calculated using Bacterial Foraging Algorithm($)**
1	1368.0	1616.77	1679.2
2	572.7	741.41	778.3
3	322.9	392.69	409.12
4	386.4	613.974	660.13
5	177.5	256.979	275
6	177.5	256.979	275
7	-1126.3	-888.93	-839.2
8	-592.6	-407.85	-369

Table VII: **Comparison of Optimal lambda**

Optimal lambda using Monte carlo simulation($/MWh)[1]	**Optimal lambda using Genetic Algorithm($/MWh)**	**Optimal lambda using Bacterial Foraging Algorithm ($/MWh)**
16.35	17.9	18.2872

Table VIII: **Comparison of Optimal lambda**

	GA	**BFA**
CPU time in sec	0.37	3.2

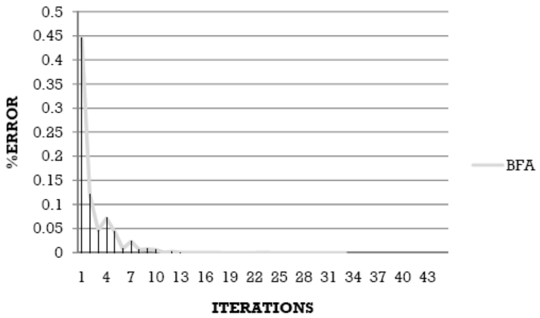

Fig. 5 Convergence criterion of BFA

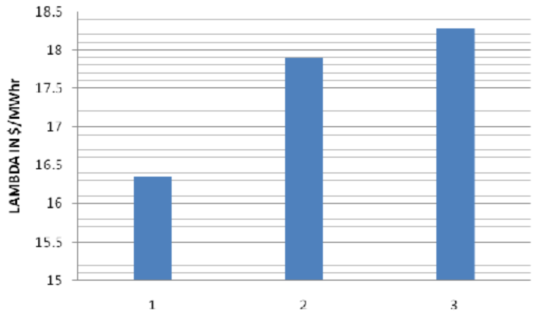

Fig. 6 comparison of lambda by three methods

1:Lambda Calculation using Monte Carlo
2:Lambda Calculation using GA
3:Lambda Calculation using BFA

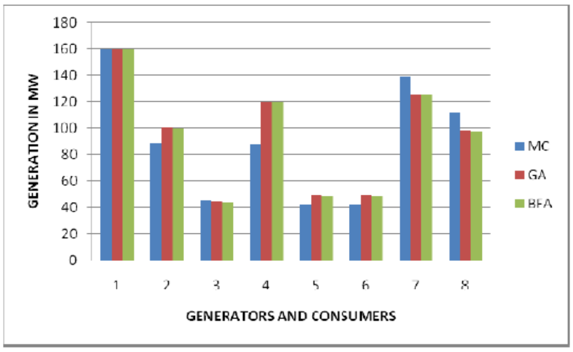

Fig. 7 comparison of power generations

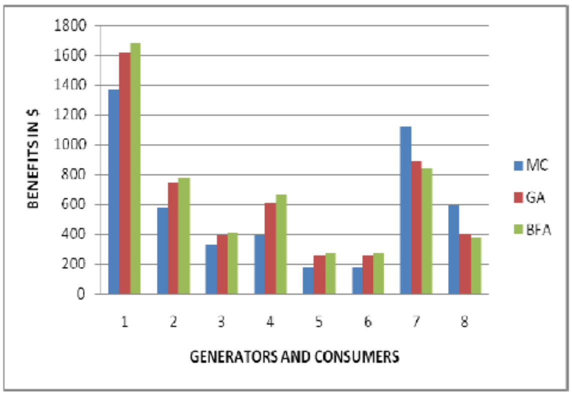

Fig. 8 comparison of benefits

VI. CONCLUSIONS

Genetic Algorithm, BFA with multi round auction bidding is efficiently used to solve the optimal bidding strategy problem. This proposed algorithm gives better results compared to Monte Carlo simulation.GA takes less computing time and better benefit compared to Monte Carlo simulation. Among the three methods BFA gives the benefit of 5286 whereas GA and Monte Carlo gives the benefits of 5169 and 4723. BFA gives the clearing price of 18.28 which is higher when compared to market clearing price obtained using GA and Monte Carlo whose market clearing prices are respectively 17.9 and 16.35 respectively. The proposed algorithms can be easily used to determine the optimal bidding strategy in different market rule, different fixed load, different capacity of buyers and sellers.
For future work, here plan to expand this algorithm using Fuzzy Adaptive Bacterial Foraging Algorithm.

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