
J Vijaya Kumar¹ and D.M. Vinod Kumar²
¹,² Department of Electrical Engineering, National Institute of Technology Warangal, A.P-506004, INDIA
E-mail: jvkeee@gmail.com

Abstract—This paper proposes a novel optimization algorithm Varying Population based Bacterial Foraging Algorithm (VPBFA) to solve optimal bidding strategy in a pool based electricity market. In a power market, Generating Companies (suppliers) participate in the bidding process in order to maximize their profits. Each supplier bid strategically for choosing the bidding coefficients to counter the competitors bidding strategy. Most of the Evolutionary Algorithms (EAs) are based on fixed population evolution, which does not attain the full potential of effective search and demands a large amount of computation. In this paper, a varying population algorithm is developed from the study of bacterial foraging behavior. This algorithm, for the first time, explores the underlying mechanisms of bacterial chemotaxis, quorum sensing and proliferation etc., which have been successfully combined into the varying-population frame. The VPBFA algorithm has been applied to the optimal bidding strategy problem and it has been evaluated by simulation studies, which were undertaken on 75-bus Indian practical system, in comparison with fixed population based algorithms like Bacterial Foraging Algorithm (BFA), Particle Swarm Optimization (PSO), Genetic Algorithm (GA) and conventional optimization method called Golden Section Search (GSS) method. The results affirmed the robustness and competence of proposed methodology over BFA, PSO and GA.

Keywords—Electricity market, Bidding strategies, Market Clearing Price (MCP), Bacterial Foraging, Varying Population.

I. INTRODUCTION

INTRODUCTION of competition on electricity markets increases efficiency and the economic growth while lowering the cost of electricity to consumers. But the sudden changes in the electricity markets have a variety of new issues such as oligopolistic nature of the market, supplier’s strategic bidding, market power misuse, price-demand elasticity and so on. Theoretically, in a perfectly competitive market, supplier should bid at their marginal production cost to maximize payoff [1]. However, practically the electricity markets are oligopolistic nature, and power suppliers may seek to increase their profit by bidding a price higher than marginal production cost. Knowing their own costs, technical constraints and their expectation of rival and market behavior, suppliers face the problem of constructing the best optimal bid. This is known as a strategic bidding problem.

In general, there are three basic approaches to model the strategic bidding problem viz. i) based on the estimation of market clearing price ii) estimation of rival’s bidding behavior and iii) on game theory. David [2] developed a conceptual optimal bidding model for the first time in which a Dynamic Programming (DP) based approach has been used. Gross and Finaly adopted a Lagrangian relaxation-based approach for strategic bidding in England-Wales pool type electricity market [3]. Jainhui et al. [4] used evolutionary game approach to analyzing bidding strategies by considering elastic demand. Ebrahim and Galiana developed Nash equilibrium based bidding strategy in electricity markets [5]. David and Wen [6] proposed to develop an overall bidding strategy using two different bidding schemes for a day-ahead market using Genetic Algorithm (GA). The same methodology has been extended for spinning reserve market coordinated with energy market by David and Wen [7]. Ugedo et al. developed a stochastic-optimization approach for submitting the block bids in sequential energy and ancillary services markets and uncertainty in demand and rival’s bidding behavior is estimated by stochastic residual demand curves based on decision trees [8]. To construct linear bid curves in the Nord-pool market stochastic programming model has been used by Fleten et al. [9]. The opponents’ bidding behaviors are represented as a discrete probability distribution function solved using Monte Carlo method by David and Wen [10].

The deterministic approach based optimal bidding problem was solved by Hobbs et al. [11], but it is difficult to obtain the global solution of bi-level optimization problem because of non-convex objective functions and non-linear complementary conditions to represent market clearing. These difficulties are avoided by representing the residual demand function by Mixed Integer Linear Programming (MILP) model [12, 13], in which unit commitment and uncertainties are also taken into account. The generators associated to the competitors’ firms have been explicitly modeled as an alternative MILP formulation based on a binary expansion of the decision variables (price and quantity bids) by Pereira et al. [14]. Jain and Srivastava considered risk constrained bidding strategy and solved using GA [15]. Ahmet et al. proposed PSO to determine bid prices and quantities under the rules of a competitive power market [16]. Kanakasabhapathy and Swarup [17] developed strategic bidding for pumped-storage hydroelectric plant using evolutionary tristate PSO. Bajpai et al. developed block bid model bidding strategy in a uniform price spot market using Fuzzy Adaptive Particle Swarm optimization (FAPSO) [18]. Venkaih et al used Fuzzy Adaptive Bacterial Foraging Algorithm (FABFA) for optimal rescheduling of active power of generators [19]. The combination of PSO and Simulated Annealing (SA) is used to predict the bidding strategy of generation companies [20]. Fevrier et al. developed a new
hybrid approach by combing the advantages of PSO and GA using fuzzy logic [21]. Azadeh et al. formed optimal bidding problem for day-ahead market as a multi objective problem and solved using GA [22].

In general, strategic bidding is an optimization problem that can be solved by various conventional and non-conventional (heuristic) methods. However, conventional methods do not guarantee finding the global optimum solution since they are more are less rely on the convexity of the objective function which, would not be always satisfied in many practical cases. In most cases, the traditional methods are suitable for single-peak and linear objective functions. To tackle this problem, Evolutionary Algorithms (EAs) have been applied to solve the optimal bidding strategy problem. These algorithms are all based on fixed population evolution, which limits their computational capability and introduces redundant computation in the optimization process. Therefore a varying population algorithm is proposed to overcome the above drawbacks.

In this paper, Varying Population based Bacterial Foraging Algorithm (VPBFA) is proposed for solving the optimal bidding strategy problem. However, instead of simply describing chemotactic behavior into the algorithm, VPBFA also incorporates the mechanism of bacterial proliferation and quorum sensing, which allows a varying population in each generation of bacterial foraging process. The VPBFA has been evaluated on optimal bidding strategy problem, focusing on maximization of the profit of the suppliers in comparison with BFA, PSO and GA. The VPBFA has already shown better results for the standard benchmark functions [24]. The evolution of the algorithm was carried out using 75-bus Indian practical system. The simulation results are reported in this paper to show the merits of the proposed algorithm.

The paper is organized as follows. Section II introduces the mathematical formulation of optimal bidding problem. Section III presents the detailed description of VPBFA and application of VPBFA to the optimal bidding problem. Section IV reports the case studies solving optimal bidding problem using VPBFA for 75-bus Indian practical system and Section V summed up the final outcome of the paper as Conclusion.

II. PROBLEM FORMULATION FOR OPTIMAL BIDDING STRATEGY

In generation bidding scheme also called single auction, only suppliers are allowed to bid in the Power Exchange (PX) auction. Consider a system consist of ‘m’ suppliers and assume that each supplier is required to bid a linear supply function to PX [10]. Suppose for ith supplier bid, linear supply curve denoted by \( G_i(P_i) = a_i + b_i P_i \) for \( i = 1, 2, ..., m \), where \( P_i \) is the active power output, \( a_i \) and \( b_i \) are non-negative bidding coefficients of the ith supplier. After receiving bids from the suppliers, the PX determines a set of generation outputs that meets the load demand and minimizes the total purchasing cost. It is clear that generation dispatching should satisfy the following Eq. (1), (2) and (3).

\[
a_i + b_i P_i = R \quad i = 1, 2, ..., m \quad (1)
\]

\[
\sum_{i=1}^{m} P_i = Q(R) \quad (2)
\]

\[
P_{\text{min},i} \leq P_i \leq P_{\text{max},i} \quad i = 1, 2, ..., m \quad (3)
\]

Where, \( R \) is the Market Clearing Price (MCP) of electricity to be determined, \( P_{\text{min},i} \) and \( P_{\text{max},i} \) are the generation output limits of the ith supplier. \( Q(R) \) is the aggregate pool load forecast as follows:

\[
Q(R) = Q_o - KR \quad (4)
\]

Where \( Q_o \) is a constant number and \( K \) is a non-negative constant used to represent the load price elasticity. When the inequality constraint Eq. (3) is ignored, the solution to Eq. (1) and (2) are,

\[
R = \frac{Q_o + \sum_{i=1}^{m} a_i}{\sum_{i=1}^{m} b_i + K} \quad (5)
\]

\[
P_i = \frac{R - a_i}{b_i} \quad i = 1, 2, ..., m \quad (6)
\]

The ith supplier has the cost function denoted by \( C_i(P_i) = e_i P_i + f_i P_i^2 \), where \( e_i \) and \( f_i \) are the cost coefficients of the ith supplier. The profit maximization objective of the ith supplier (\( i = 1, 2, ..., m \)) in a unit time for building bidding strategy can be described as:

Maximize: \( F(a_i, b_i) = R P_i - C_i(P_i) \quad (7) \)

Subject to: Eq. (5) and (6)

The objective is to determine bidding coefficients \( a_i \) and \( b_i \) so as to maximize \( F(a_i, b_i) \) subject to the constraints Eq. (5) and (6).

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 day bidding period is confidential in which suppliers cannot solve optimization problem given in Eq. (7) directly. However, bidding information of previous day will be disclosed after Independent System Operator (ISO) decide MCP and everyone can make use of this information to strategically bid for the next hour of the present day transaction between suppliers. An immediate problem for each supplier is how to estimate the bidding coefficients of rivals.

The bidding coefficients \( a_i \) and \( b_i \) are interdependent; therefore one of the coefficient make as a constant and other is randomly varied using probability density function (pdf). The probability density function of a continuous random variable is a function which can be integrated to obtain the probability that the random variable takes a value in a given interval. Let, from the ith supplier’s point of view, rival’s ith (\( \neq i \)) bidding
coefficients \((a_i, b_i)\) obey a joint normal distribution with pdf given by:

\[
pdf_{p}(a_i, b_i) = \frac{1}{2\pi \sigma^{(a)}_{i} \sigma^{(b)}_{i} \sqrt{1 - \rho^2_i}} \exp \left\{ - \frac{1}{2(1 - \rho^2_i)} \left[ \frac{(a_i - \mu^{(a)}_{i})^2}{\sigma^{(a)}_{i}^2} + \frac{(b_i - \mu^{(b)}_{i})^2}{\sigma^{(b)}_{i}^2} - 2\rho_i (a_i - \mu^{(a)}_{i})(b_i - \mu^{(b)}_{i}) \frac{\sigma^{(a)}_{i}}{\sigma^{(b)}_{i}} \right] \right\} \tag{8}
\]

Where, \(\rho_i\) is the correlation coefficient between \(a_i\) and \(b_i\), \(\mu^{(a)}_{i}\), \(\mu^{(b)}_{i}\), \(\sigma^{(a)}_{i}\) and \(\sigma^{(b)}_{i}\) are the parameter of the joint distribution. The marginal distributions of \(a_i\) and \(b_i\) are both normal with mean values \(\mu^{(a)}_{i}\) and \(\mu^{(b)}_{i}\), and standard deviations \(\sigma^{(a)}_{i}\) and \(\sigma^{(b)}_{i}\) respectively.

Based on historical bidding data these distributions can be determined for all the suppliers [10]. The probability density function Eq.(8) represents the joint distributions between \(a_i\) and \(b_i\), the task of optimally coordinating the bidding strategies for a supplier with objective function Eq.(7), and constraints (5) and (6), becomes a stochastic optimization problem.

III. PROPOSED VARYING POPULATION BASED BACTERIAL FORAGING ALGORITHM (VPBFA)

Based on bacterial behaviors, a VPBFA model comprises of the following four aspects, i.e., chemotaxis, metabolism energy and nutrition losing, proliferation and elimination, and a simplified quorum sensing. Chemotaxis is the basic search principle of VPBFA. The metabolism energy and nutrition losing phenomenon lead to the bacterial proliferation and elimination, which cause the variation population sizes [25]. By using the above features, VPBFA can be used to tackle optimal bidding strategy problem.

A. Chemotaxis

Bacteria swim by rotating thin, helical filaments known as flagella driven by a reversible motor embedded in the cell wall. Peritrichously flagellated bacteria such as E. coli have 8-10 flagella placed randomly on the cell body. Swimming was found to consist of smooth “runs” interrupted roughly every second by transient “tumble”. Chemotaxis is the ability of the cells to move toward distant sources of food molecules, and it is based on the suppression of tumbles in cells. Based on the bacterial chemotactic behaviour, BFA has been proposed in [23]. In BFA, nourishment environment stands for an optimization objective function, and the BFA algorithm imitates bacterial swimming motions.

\[
\theta_i(t_c) = \theta_i + c(t) \frac{\Delta t}{\sqrt{\Delta t^2}} \tag{9}
\]

Let \(\theta_i(t_c)\) be the location of the \(i^{th}\) bacterium at the \(t^{th}\) chemotactic step, then the updated position of the next movement after a tumble is:

\[
\theta_i(t_c + 1) = \theta_i(t_c) + c(t) \frac{\Delta t}{\sqrt{\Delta t^2}} \tag{10}
\]

Where \(\Delta t\) indicates the \(i^{th}\) step tumble angle, which can be expressed as:

\[
\Delta t = [\Delta t_1, \Delta t_2, ..., \Delta t_n] \tag{11}
\]

Where \(n\) denotes the size of dimensions. The length of \(c(t)\) can be expressed as:

\[
\sum_{i=1}^{p} \left( E_i(t_c) - \frac{\min\{E(t_c)\}}{\max\{E(t_c)\} - \min\{E(t_c)\}} \right) \tag{12}
\]

Where \(E(t_c)\) is the set of fitness values at the \(t^{th}\) chemotactic step, which can be expressed as:

\[
E(t_c) = \{ E_{1}(t_c), E_{2}(t_c), ..., E_{p}(t_c) \} \tag{13}
\]

Where \(p\) is the population size of current generation. In equation (10), \(c(t)\) is a positive number which is in the range of \((0, 1)\). In the simulation, \(c(t)\) decreases during the optimization. Thus, the dynamic \(c(t)\) accelerates the speed of convergence, and increases the convergence accuracy.

B. Metabolism energy and Nutrition Losing

Bacterial metabolism can be broadly divided on the basis of energy usage for chemotaxis, growth and sensing. In VPBFA, the bacterial energy is described as \(E_i(t_c)\), which is a measure of the energy quantity. \(E_i(t_c)\) indicates the energy of the \(i^{th}\) bacterium at the \(t^{th}\) chemotactic step. The evaluation value \(E_i(t_c)\) is the source for the bacterial energy.

For the algorithm implemented, the record of nutrition losing is updated at each evaluation. At each evaluation step, the quantity of nutrition losing record has been subtracted from the fitness value, i.e., the value of optimum decreases when bacteria sink into that position. If there is not enough nutrition in that position, the bacteria have a tendency to swim to a forane space. Pre-mature results are then prevented with this method. After \(h\) iterations of the function evaluated, the geometrical center of each nutrient losing area can be expressed as:

\[
G = \left\{ g_m = [g_{1m}, g_{2m} ..., g_{nm}] | m = 1, 2, ..., h \right\} \tag{14}
\]

Where \(g_m\) indicates the \(m^{th}\) geometrical center of nutrition losing area, and \(g_{nm}\) indicates the \(m^{th}\) geometrical center on \(n^{th}\) dimension.

Set \(X_i = [x_{i1}, x_{i2}, ..., x_{in}]\) as the coordinate of \(i^{th}\) bacterium, and assume bacterium \(i\) falls into the geometrical area \(m\), then the distance between the bacterium and the geometrical center is less than the radius of that area. This can be expressed as:

\[
|X_i - g_m| < \varepsilon \tag{15}
\]
where \( c \) is normalized radius of each area. When the \( i^{th} \) bacterium falls into several overlaps of the geometrical area, the energy incremental quantity is:

\[
\Delta e_i(t_c) = s \cdot e_b
\]

(16)

Where \( s \) denotes the numbers of the geometrical area, and \( e_b \) represents the unit quantity of energy. The energy transferred from the environment to a bacterium for metabolism is denoted as \( \Delta e_i(t_c) \). Thus, for a bacterium, the updated energy after chemotactic step \( t_c \) is defined as:

\[
e_i(t_c + 1) = e_i(t_c) + \Delta e_i(t_c)
\]

(17)

Due to the nutrition losing, \( s \cdot e_b \) is subtracted from the evaluation value for the bacterium \( i \).

C. Proliferation and Elimination

All bacteria reproduce through binary fission, which results in cell division. Two identical clone daughter cells are produced after the cell division. In VPBFA, the reproduction process is controlled by the bacterial energy \( e_i(t_c) \) and the elimination is determined by the bacterial foraging process \( t_c \). When \( e_i(t_c) \) approaches to the upper limit of the energy boundary, the bacteria will will turn into reproduction states.

For the new bacterium, the bacterial energy for each bacterium is:

\[
e_{p+1}(t_c + 1) = \frac{e_i(t_c)}{2}
\]

(18)

where \( p \) is the population size in the current state. The previous \( i^{th} \) bacterium also keeps half of the energy:

\[
e_i(t_c + 1) = \frac{e_i(t_c)}{2}
\]

(19)

In VPBFA, a counter is set to record the bacterial age for each bacterium. After the evaluation process, the counter is increased by 1. After the cell division, the ages of two new cells are set to 0. For an individual, when the bacterial age exceeds the upper limit of its lifespan, it will be eliminated from the searching space. Meanwhile, the position of the dead cell will be tracked.

The bacteria age is updated using the following equation:

\[
A_i(t_c + 1) = A_i(t_c) + 1,
\]

(20)

where \( A_i(t_c) \) is the age counter

From Eq.(9), it can be deduced that the bacteria tend to stay around the optima and the eliminated bacteria sink around the optima.

D. Simplified Quorum Sensing

The bacterial sensors are the receptor proteins that are signalled directly by external substances or via the piroplasmic substrate-binding proteins [23]. Bacteria use sensing to produce and secrete certain signalling compounds (called auto inducers or pheromone). These bacteria also have a receptor that can specifically detect the pheromone. When the inducer binds the receptor, it activates the transcription of certain genes, including those for inducer synthesis. Bacteria use signalling molecules which are released into the environment. As well as releasing the signalling molecules, bacteria are also able to measure the number of the molecules within a population.

Bacteria can obtain more nutrition around the optima. Based on this assumption, the density of the pheromone is increased at the position, where the fitness value is maximum. Each individual is attracted by the pheromone randomly. The mathematical description is:

\[
\theta_i(t_c) = \theta_i(t_c) + \delta \cdot \theta_{best}(t_c) - \theta_i(t_c)
\]

(21)

Where \( \delta \) indicates a gain parameter for the bacterial attraction, \( \theta_{best}(t_c) \) indicates the position of global best solution on \( i^{th} \) optimization process, and \( \theta_i(t_c) \) is the current position of the \( i^{th} \) bacterium.

The flow chart of the proposed VPBFA shown in Fig. 1.

---

**Figure 1**: Flow chart for the proposed Varying population based Bacterial Foraging Algorithm (VPBFA)

---

**IV. RESULTS AND DISCUSSIONS**

In order to evaluate the performance of the proposed method for solving optimal bidding problem for generation bidding, 75-bus Indian practical system is considered [26]. The performance of VPBFA has been compared with BFA [23], PSO [16], GA [15] and a traditional optimization method called Golden Section Search (GSS) method [6]. In this work, the parameters used for BFA, PSO and GA (binary coded) are given in Table I. Simulations are carried on 2.66GHz, PIV Processor, 3GB RAM and MATLAB 7.8 version is used.
S: population size, Ne: no. of chemotactic steps, Ns: Swimming length, Nr: no. of reproduction steps, Ned: no. of elimination-dispersal, C(i): Run length vector, Ped: Probability of elimination-dispersal for BFA; c1, c2: learning factors, w: inertia weight for PSO; Pe: Elitism Probability, Pc: Crossover probability, Pm: mutation probability. l: length of the chromosome for GA;

The test system consists of 15 suppliers, who will supply electricity to aggregate load. Q, is 3000 with inelastic load (K=0), considered for aggregated demand. Bidding strategies are shown in Table II. The optimal bid prices and profits are shown in Table III. It can be evident from Tables II and III that, proposed VPBFA method producing higher profits compared with other reported constant population evolutionary algorithms. Therefore, the bidding parameters obtained by VPBFA are optimum compared to BFA, PSO, GA and GSS method. The best result, average results and percentage deviation of VPBFA, BFA, PSO and GA from 20 runs are shown in Table IV. It is observed that the average profit using proposed approach is more than the reported methods. It also observed that the percentage deviation of proposed method is less compared to the reported methods, which shows the robustness of the proposed method. Fig. 2 shows the variation of population size of VPBFA within 100 iterations. The time taken for the convergence of the proposed method is drastically reduced because the attraction among bacteria offered by quorum sensing in VPBFA is effective, which leads to a fast convergence rate compared to reported methods. The Percentage Deviation (PD) expressed as:

\[ PD = \frac{(Best - Worst)}{Best} \times 100\% \]

V. CONCLUSIONS

In this paper, a novel optimization algorithm, Varying Population based Bacterial Foraging Algorithm (VPBFA), has been presented. The algorithm is based upon the bacterial foraging, proliferation, elimination, and quorum sensing behaviors. In contrast to the fixed population based EAs, VPBFA has a varying population which was introduced by simulating the phenomena of cells’ split and contributes significantly to global search. The algorithm has also incorporated the tumble and run actions of chemotactic process, which greatly enhances the local search capability of the algorithm. The simulation studies have been carried out on 75-bus Indian practical system for generation bidding which aims to maximize the total profit. The results show that VPBFA can provide improved solutions for generation bidding than BFA, PSO and GA in terms of optimization accuracy and computation robustness.

REFERENCES


TABLE I Parameters for Different Approaches

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Population size = 100, Max. iterations=100, Life span = 50 generations, Maximum length of a swim = 10</td>
<td>S=100; Np=30; Nc=10; Nc,=10; C1,=0.5; P,=0.1; cx=c2=2.0; w=1 to 0.4</td>
<td>Population size = 100; Generations =100; l=12</td>
<td>P,=0.85; Pr=0.005</td>
</tr>
<tr>
<td>No. of particles=100; Max. iterations=100</td>
<td>2134.78</td>
<td>2218.50</td>
<td>0.037</td>
</tr>
</tbody>
</table>

TABLE II Bidding Strategies of suppliers

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>b,</td>
<td>b,</td>
<td>b,</td>
<td>b,</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.009742</td>
<td>0.005508</td>
<td>0.002700</td>
<td>0.002944</td>
<td>0.001993</td>
</tr>
<tr>
<td>2</td>
<td>0.016518</td>
<td>0.013060</td>
<td>0.003232</td>
<td>0.004774</td>
<td>0.003233</td>
</tr>
<tr>
<td>3</td>
<td>0.009608</td>
<td>0.006945</td>
<td>0.006976</td>
<td>0.003918</td>
<td>0.002653</td>
</tr>
<tr>
<td>4</td>
<td>0.009887</td>
<td>0.001473</td>
<td>0.006762</td>
<td>0.002844</td>
<td>0.001926</td>
</tr>
<tr>
<td>5</td>
<td>0.147538</td>
<td>0.489401</td>
<td>0.134363</td>
<td>0.196915</td>
<td>0.133432</td>
</tr>
<tr>
<td>6</td>
<td>0.004233</td>
<td>0.016044</td>
<td>0.011002</td>
<td>0.005410</td>
<td>0.003664</td>
</tr>
<tr>
<td>7</td>
<td>0.012385</td>
<td>0.017693</td>
<td>0.006162</td>
<td>0.012333</td>
<td>0.008216</td>
</tr>
<tr>
<td>8</td>
<td>0.007337</td>
<td>0.008636</td>
<td>0.009800</td>
<td>0.004973</td>
<td>0.003367</td>
</tr>
<tr>
<td>9</td>
<td>0.008135</td>
<td>0.002150</td>
<td>0.008323</td>
<td>0.004177</td>
<td>0.002828</td>
</tr>
<tr>
<td>10</td>
<td>0.006934</td>
<td>0.002597</td>
<td>0.003392</td>
<td>0.003222</td>
<td>0.002182</td>
</tr>
<tr>
<td>11</td>
<td>0.007108</td>
<td>0.003358</td>
<td>0.002925</td>
<td>0.003222</td>
<td>0.002182</td>
</tr>
<tr>
<td>12</td>
<td>0.008369</td>
<td>0.002256</td>
<td>0.005573</td>
<td>0.003063</td>
<td>0.002074</td>
</tr>
<tr>
<td>13</td>
<td>0.002320</td>
<td>0.001947</td>
<td>0.002035</td>
<td>0.002964</td>
<td>0.002007</td>
</tr>
<tr>
<td>14</td>
<td>0.002432</td>
<td>0.003704</td>
<td>0.005630</td>
<td>0.002665</td>
<td>0.001805</td>
</tr>
<tr>
<td>15</td>
<td>0.009649</td>
<td>0.007303</td>
<td>0.002529</td>
<td>0.003640</td>
<td>0.002465</td>
</tr>
</tbody>
</table>

TABLE III Market Clearing Price (MCP) (Rs/MWh) and Profit (Rs) of Generators

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>P (MW)</td>
<td>Profit(Rs)</td>
<td>P (MW)</td>
<td>Profit(Rs)</td>
<td>P (MW)</td>
<td>Profit(Rs)</td>
</tr>
<tr>
<td>1</td>
<td>431.624</td>
<td>143.13</td>
<td>199.78</td>
<td>199.78</td>
<td>157.43</td>
</tr>
<tr>
<td>2</td>
<td>49.1724</td>
<td>34.13</td>
<td>73.46</td>
<td>42.63</td>
<td>175.4</td>
</tr>
<tr>
<td>3</td>
<td>79.3329</td>
<td>48.07</td>
<td>71.74</td>
<td>51.50</td>
<td>174.1</td>
</tr>
<tr>
<td>4</td>
<td>94.84</td>
<td>172.55</td>
<td>100</td>
<td>214.12</td>
<td>92.6</td>
</tr>
<tr>
<td>5</td>
<td>111.06</td>
<td>5.94</td>
<td>165.22</td>
<td>4.05</td>
<td>170.3</td>
</tr>
<tr>
<td>6</td>
<td>98.95</td>
<td>59.90</td>
<td>73.9</td>
<td>43.27</td>
<td>54.2</td>
</tr>
<tr>
<td>7</td>
<td>60</td>
<td>256.00</td>
<td>45.62</td>
<td>245.86</td>
<td>60</td>
</tr>
<tr>
<td>8</td>
<td>76.59</td>
<td>90.25</td>
<td>70.62</td>
<td>73.72</td>
<td>77.2</td>
</tr>
<tr>
<td>9</td>
<td>409.67</td>
<td>72.59</td>
<td>389.1</td>
<td>7.59</td>
<td>227.7</td>
</tr>
<tr>
<td>10</td>
<td>79.74</td>
<td>122.36</td>
<td>80</td>
<td>26.90</td>
<td>80</td>
</tr>
<tr>
<td>11</td>
<td>100.69</td>
<td>141.72</td>
<td>109</td>
<td>156.34</td>
<td>109</td>
</tr>
<tr>
<td>12</td>
<td>597.42</td>
<td>266.17</td>
<td>585.73</td>
<td>358.62</td>
<td>252.5</td>
</tr>
<tr>
<td>13</td>
<td>514.64</td>
<td>334.22</td>
<td>487.52</td>
<td>241.98</td>
<td>603.4</td>
</tr>
<tr>
<td>14</td>
<td>150</td>
<td>404.31</td>
<td>150</td>
<td>390.40</td>
<td>150</td>
</tr>
<tr>
<td>15</td>
<td>86.2501</td>
<td>58.16</td>
<td>147.34</td>
<td>61.89</td>
<td>302.1</td>
</tr>
<tr>
<td>Total Profit</td>
<td>7.93</td>
<td>7.87</td>
<td>7.68</td>
<td>7.56</td>
<td>7.38</td>
</tr>
</tbody>
</table>

TABLE IV Performance Comparison of Different Approaches

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Profit (Rs)</td>
<td>2218.5</td>
<td>2118.65</td>
<td>1751.92</td>
</tr>
<tr>
<td>Best (Rs)</td>
<td>2218.5</td>
<td>2118.65</td>
<td>1751.92</td>
</tr>
<tr>
<td>Worst (Rs)</td>
<td>2134.78</td>
<td>1986.81</td>
<td>1627.34</td>
</tr>
<tr>
<td>Average (Rs)</td>
<td>2176.64</td>
<td>2052.73</td>
<td>1689.63</td>
</tr>
<tr>
<td>PD (%)</td>
<td>0.037</td>
<td>0.062</td>
<td>0.071</td>
</tr>
<tr>
<td>Average Execution Time (sec)</td>
<td>2.38</td>
<td>67.31</td>
<td>78.37</td>
</tr>
</tbody>
</table>

Figure 2 Varying population size in proposed VPBFA