# BACTERIAL FORAGING-BASED ALGORITHM OPTIMIZATION BASED ON FUZZY MULTI-OBJECTIVE TECHNIQUE FOR OPTIMAL POWER FLOW DISPATCH

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**ABSTRACT:** *This paper presents a multi-objective bacterial foraging-based algorithm (BFA) to solve the optimal power flow (OPF) problem. OPF problem has been treated as a multi-objective constrained optimization problem. In this paper Different objective functions have been considered in the problem formulation, which are fuel emission, power losses, voltage deviation and generation cost considering valve effect while there are both continuous and discrete control variables included in the objective functions. To handle the multi objective optimization problem, fuzzy strategy is embedded into the optimization algorithm. This tragedy has many advantages like eliminating the problem of choosing the penalty factors for constraints and behaves them just like objective functions***.** *Other evolutionary algorithm which is considered for comparison is conventional particle swarm optimization (CPSO). Simulation results on IEEE-30 bus test system show the effectiveness of the proposed approach in solving multi-objective OPF.*
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**Key Words:** *Bacterial foraging-based algorithm, Fuzzy modeling, Multi-objective optimal power flow, Voltage security margin, Fuel emission, Fuel cost, Valve effect, Power losses*

## 1. INTRODUCTION

Optimal power flow (OPF) has been worked for nearly four decades by researcher, since Carpentier presented the well-defined OPF formulation in the early 1962 [1].

Classical optimization methods for OPF problems are suffering from the issue of initial conditions. They may either converge to local optimum solutions or, diverge in their solution processes. These classical optimization methods are also limited in handling algebraic functions and unable to consider dynamic characteristics and to deal with differential equations. Various optimization techniques such as nonlinear programming (NLP), quadratic programming (QP), interior point method (IPM), linear programming and hybrid versions, Newton method and sequential unconstrained minimization have been implemented to solve OPF problem [2-4]. These classical optimization are limited to differentiable convex and continues algebraic objective functions and constraints and may depend on the specific function and/or constraints [5]. On the other hand, due to nature of these methods, they might converge to local solutions and fail to achieve the global one [6]. Furthermore, as the objective function complexity increases, these methods become more unreliable.

Since 1993, some of these drawbacks have been eliminated by modifying and improving some of classical approaches and using new category of optimization tools. Modern heuristic optimization techniques such as evolutionary algorithms have been successfully applied to many power system optimization problems already. Therefore to overcome these difficulties in optimization, the application of modern heuristic methods is suggested. Evolutionary algorithms (EAs) [7-10], Simulated Annealing (SA) [11], Artificial Neural Network (ANN) [12-15] and Tabu Search Algorithm (TSA) [16], dual-type method [17, 18], mean field theory [19] and ordinal optimization theory [20].

Recently, EAs such as genetic algorithms (GAs), particle swarm optimization (PSO), Differential evolutionary (DE) and bacterial foraging-based algorithm (BFA) have made more contributions to solve OPF problem than other methods.

Although GA discovers the promising regions of search space quickly, it has two usual drawbacks: exploitation inability and premature convergence [21]. PSO algorithm is a swarm intelligent technique inspired by food searching behavior of bird flocking [22, 23]. This algorithm has been widely used in various fields of power system such as active power control [24], reactive power and voltage control [25-27], power loss optimization [28] and voltage stability improvement. DE algorithm is a simple population based evolutionary algorithm [29]. DE is also used to solve problems in power system [30, 31]. DE extracts the differential information (i.e., distance and direction information) from the current population of solutions to guide its further search. However, DE has no mechanism to extract and use global information about the search space [32].

In this paper, a new solution for OPF problem known as bacterial foraging-based algorithm (BFA) is proposed. BFA is a meta-heuristic optimization method which has been recently proposed [33, 34]. BFA combines the benefits of the genetic-based memetic algorithms (MAs) and the social behavior-based PSO algorithm [35]. The algorithm is based on foraginr behavior of E.coil bacteria present in human intestine.

The rest of this paper is organized as follows: Section 2 presents the mathematical formulation of OPF problem. In section 3, BFA optimization is described in detail. Simulation results are given in section 4. Finally, conclusions are presented in section 5.

## 2. PROBLEM FORMULATION

The objective functions (F), and constraints of OPF problem (g), can be mathematically modeled as follows:

$$Min\ F(\vec{X},\vec{U})$$
$$g(\vec{X},\vec{U})=0 \qquad (1)$$
$$h_{\min}<h(\vec{X},\vec{U})<h_{\max}$$

where $\vec{X}$ and $\vec{U}$ denotes the state and control variables respectively. The state vector includes bus voltage magnitudes $V_L$ and generator reactive power $Q_G$, i.e., $\vec{X}=[V_L\ \ Q_G]^T$. The control variable vector consists of injected active power $P_G$, generator terminal voltage $V_G$, transformer tap ratio $T_k$ and reactive power injection of capacitor banks $Q_c$, i.e., $\vec{U}=[P_G\,V_G\,T_R\,Q_C]^T$.

### 2.1. Objective Function

The studied objective functions in this paper present the fuel cost and fuel emission of generation, active power loss and voltage deviation which are described as follows:

**i. Fuel cost**

The aim of first objective function is to optimize the fuel cost of generators. This function can be presented as follows:

$$F=\sum_{i=1}^{N}(a_i+b_iP_i+c_iP_i^2)\quad \$/h \qquad (2)$$

where $a_i$, $b_i$, $c_i$ are the fuel cost coefficients, $P_i$ is the injected active power at bus i (p.u.), and N is the Number of PV buses.

To consider the valve point loading effect in this objective function, () should be modified in this manner [2], [35]:

$$F=\sum_{i=1}^{N}[a_i+b_iP_i+c_iP_i^2+e_i\sin(f_i(P_i^{\min}-P_i))]\quad \$/h \qquad (3)$$

where $e_i$, $f_i$ are the valve effect coefficients.

**ii. Power Loss**

The second objective function tends to minimize the active power loss in the transmission network which can be described as:

$$P_L=\sum_{k=1}^{N_L}g_k\left[\left|V_i^2\right|+\left|V_j^2\right|-2\left|V_i\right|\left|V_j\right|\cos(\delta_i-\delta_j)\right] \qquad (4)$$

where $g_k$ is the conductance of branch k (p.u.), $V_i$ is the voltage magnitude of bus i (p.u.), $\delta_i$ is the angle of bus i(rad), and NL is the number of transmission Lines.

**iii. Fuel emission**

The following equation describes the equation of the third objective function:

$$E=\sum_{i=1}^{N}\ \alpha_i+\beta_iP_i+\gamma_iP_i^2\quad ton/h \qquad (5)$$

where $\alpha$i, $\beta$i, $\gamma$i are the fuel emission coefficients.

**iv. Voltage Deviation**

The last objective function of this paper is to minimize the deviation of bus voltages from a pre-specified reference value. In this paper, 1 p.u. is assigned to reference voltage:

$$D=\sum_{i=1}^{N_d}\left|V_i-V_i^{sp}\right| \qquad (6)$$

where $N_d$ is the number of PQ buses and $V_i^{sp}$ is pre-specified value of bus voltage.

### 2.2. CONSTRAINTS

Equality constraints of this optimization problem are the active and reactive power flow equations as follows:

$$P_i-P_{D_i}-\sum_{j=1}^{n}\left|V_i\right|\left|V_j\right|\left|Y_{ij}\right|\cos(\theta_{ij}-\delta_i+\delta_j)=0$$
$$Q_i-Q_{D_i}-\sum_{j=1}^{n}\left|V_i\right|\left|V_j\right|\left|Y_{ij}\right|\cos(\theta_{ij}-\delta_i+\delta_j)=0 \qquad (7)$$

where θij is the angle of admittance between buses i and j (rad) θij, |Yij| is the magnitude of admittance between buses i and j, $P_{Di}$ is the demanded active power at bus i (p.u.), $Q_i$ is the Injected reactive power at bus i (p.u.), $Q_{Di}$ is the demanded reactive power at bus i (p.u.), and n is the number of total buses.

Inequality constraints consist of discrete and continuous constraints:

**i. Continuous constraints:**

Active and reactive power output and voltage magnitude at each bus of generators are given by:

$$P_i^{\min}\le P_i\le P_i^{\max}$$
$$Q_i^{\min}\le Q_i\le Q_i^{\max} \qquad (8)$$

Voltage magnitude of non-generative buses and transmission lines loading are given by:

$$V_i^{\min}\le V_i<V_i^{\max}$$
$$S_{L_i}\le S_{L_i}^{\max} \qquad (9)$$

where SL is the transmission line loading .

**ii. Discrete constraints**

Transformer tap ratio and switchable VAR compensation are limited to:

$$T_i^{\min}\le T_i\le T_i^{\max}$$
$$Q_{C_i}^{\min}\le Q_{C_i}\le Q_{C_i}^{\max} \qquad (10)$$

where Ti is the transformer tap ratio.

## 3. FUZZY OPTIMIZATION TECHNIQUE

The multi-objective problem is generally solved by three types of methods. One is pareto-based approach to get a set of non-dominated solutions in the process of optimization. Second is the coefficient method and the last method is transforming the multiple objective function into a single objective model and treating it through single objective strategies [36]. In the method developed by Bellman and Zadeh [37] , the single objective problem is achieved by maximizing the minimum degree of satisfaction among the membership functions. The fuzzy decision is marked out due to the intersection of fuzzy objectives and fuzzy constraints. The first operation is the fuzzification process of the merged objective function and the constraints. In this procedure, two type of function μ(x) are defined for each objective function and constraint, as shown in figure 1. In these figures, Minimum value for each objective is obtained by single objective optimization and the maximum value is specified by the initial value. In this technique, it is possible to change the effectiveness of any objective function by reducing or increasing its specified maximum value. In other words, when the specified maximum value of an objective function decreases, it is considered more important in the optimization than the previous state and vice versa. These membership functions are initially combined by “and” operator (minimum). The following equation illustrates this procedure:

$$\mu_D(x) = \min(\mu_{f1}(x), \mu_{f2}(x), ..., \mu_{c1}(x), \mu_{c2}(x), ...) \quad (11)$$

where μD(x) represents the membership function of the optimal decision function.

The membership values express the degree of satisfaction for each objective. High objective is given a low value, though low objective is assigned a high value. Hence, the multi objective problem can be transformed into the following maximization problem subject to a crisp constraint set:

$$\max \mu_D(x,u) \;\; s.t. \;\; H(x,u) = 0 \;,\; C(x,u) \le 0 \quad (12)$$

## 4. BACTERIAL FORAGING-BASED ALGORITHM

Natural selection tends to eliminate animals with poor "foraging strategies" and favor the propagation of genes of those animals that have successful foraging strategies as they are more likely to enjoy reproductive success. After many generations Poor foraging strategies are either eliminated or shaped in to good ones (reformed).

Bacteria foraging is one of the most recent evolutionary algorithms that is inspired by E.coil bacterium behavior which lives in human body.

The E.coil bacterium has a fascinating control system (guidance system) that enables it to look for food and try to avoid noxious substances.

The E.coil bacterium foraging mechanism consists of four general parts. In BFA, many characteristics of real E.coil are ignored to provide a simpler algorithm. Four general processes of E.coil foraging mechanism are chemotaxis, swarming, reproduction and elimination and dispersal events.

In this section, the BFA originally developed in [33] is presented. To do so, first the main parts of foraging mechanism are clarified and then, the implemented algorithm is described in detail.

### 4.1. Chemotaxis

The activity in which the bacteria gather in the nutrient-rich areas due to their inherent tendency is called "chemotaxis". This process if defined by a tumble that may be follows by swimming. To represent a tumble, a unit length random direction, say Φ(j), is generated; this will be used to define the direction (tumbling) in the entire lifetime of the bacterium. Also, a vector like C(i) is generated to define the size of the step taken in the specified random direction. Now, a tumble can be described as follow:

$$B\;\; i, j+1, k, l \;\; = B\;\; i, j, k, l \;\; + C\;\; i \;\; \Phi\;\; j \quad (13)$$

where B(i,j,k,l) represent the ith bacterium at jth chemotactic, kth reproductive, and lth elimination and dispersal step. If at B(i,j+1,k,l) the fitness is better (higher) than at B(i,j,k,l), then another step of size C(i) in this same direction will be taken and again, if that step resulted in a

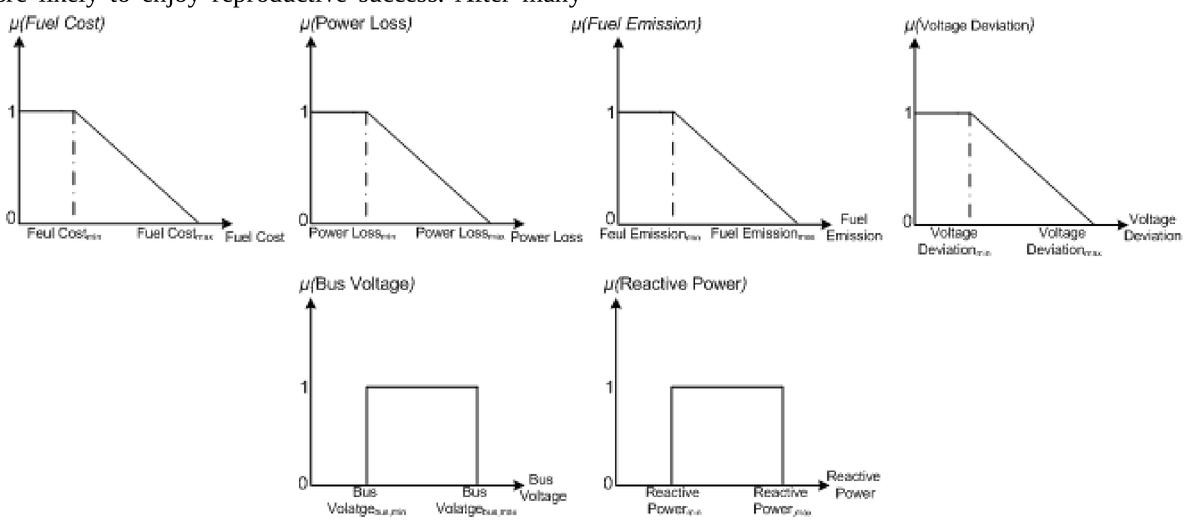


Figure. 1. Membership functions of objective functions and constraints

position with a better cost value than at the previous one, another step is taken. This swim continued as long as it continues to increase the fitness but only up to maximum number of step, Ns.

### 4.2. Swarming

It is always desired that the bacterium that has searched the optimum path of food should try to attract other bacteria so that they reach the desired place more rapidly. Swarming makes the bacteria congregate into groups and hence move as concentric patterns of groups with high bacterial density. Let dattract=0.1 be the depth of the attractant released by the cell and wattract=0.2 be a measure of the width of the attractant signal. The cell also repels a nearby cell in the sense that it consumes nearby nutrients and it is not physically possible to have two cells at the same location. To model this, we let hreplient=dattract be the height of the repellant effect (magnitude of its effect) and wattract= 0.2 be a measure of the width of the repellant. Finally

$$J_{CC}(B(n,j,k,l),B(j,k,l)) = \sum_{i=1}^{N_b} J^{i}_{CC}(B(n,j,k,l),B(i,j,k,l)) = \qquad (14)$$
$$\sum_{i=1}^{N_b}\left[-d_{attract}\exp\ -w_{attract}\sum_{m=1}^{N_v}(\theta_m^n-\theta_m^i)^2\ \right]+$$
$$\sum_{i=1}^{N_b}\left[-h_{repellant}\exp\left(-w_{attract}\sum_{m=1}^{N_b}(\theta_m^n-\theta_m^i)^2\right)\right]$$

where Jcc(θ,p(j,k,l)) is the cost function value to be added to the actual cost function to be minimized to present a time varying cost function, Nb is the total number of bacteria, Nv is the number of variables to be optimized that are present in each bacterium and $\theta^i_j$ is the jth variable of the ith bacterium.

### 4.3. Reproduction

After Nc chemotaxis steps, a reproduction step is taken. Let Nre be the number of reproductions steps. It is assumed that half of the populations have had sufficient nutrients so they can split in two (reproduce) and the least healthy bacteria die. This makes the population of bacteria constant.

### 4.4. Elimination and dispersal

It is possible that in the local environment, the life of a population of bacteria changes either gradually by consumption of nutrients or suddenly due to some other influence. Events can kill or disperse all the bacteria in the region. They have the effect of possibly destroying the chemotactic progress, but in contrast, they also can assist it, since dispersal may place bacteria near good fitness position. Elimination and dispersal help in reducing the behavior of stagnation i.e., being trapped in premature solution point or local optima. Elimination and dispersal help to avoid getting in to local minimum optima.

Now the algorithm of BF which is shown in figure 2 can be described as follows:

**i. Initialization:**

The parameters of optimization must be determined before the procedure begins. Each parameter is set according to the OPF problem in this study as shown in table 1.

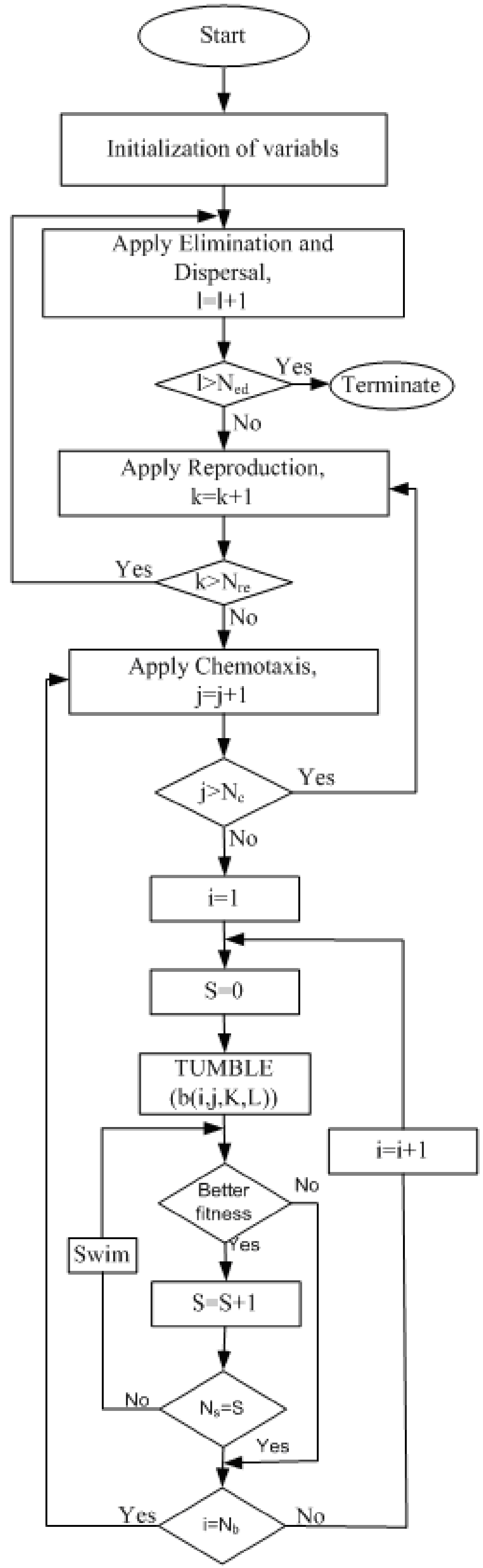


Figure 2. Flow chart of the BFA.

**ii. Iterative procedure of optimization:**

The BF iterative mechanism is described for optimization purpose:

1. $j=k=l=0$
2. Generate the initial B(i,1,1,1) randomly within feasible space for i=1,…,Nb
3. Elimination and dispersal loop: $l=l+1$
4. Reproduction loop: $k=k+1$
5. Chemotaxis loop: $j=j+1$

a) For $i=1,\ldots,N_b$, calculate cost function value for each bacterium as follows:

b) $$J_{sw}(i,j,k,l)=J(i,j,k,l)+J_{cc}(B(i,j,k,l),B(j,k,l))$$

c) Save $J_{sw}$ since a better cost might be found: $J_{last}=J_{sw}$

d) Tumble:

Generate a random vector Δ with each element Δ (m) m=1,.., Nv a random number on [-1,1].

e) Let $$B(i,j+1,k,l)=B(i,j,k,l)+C(i)\frac{\Delta}{\sqrt{\Delta^T\Delta}}$$

f) Calculate J(i,j+1,k,l) and let $$J_{sw}(i,j,k,l)=J(i,j,k,l)+J_{cc}(B(i,j,k,l),B(j,k,l))$$

g) Swim:

i. Let m=0

ii. While $M<N_s$

iii. If $J_{sw}<J_{last}$ , let $J_{last}=J_{sw}$, $m=m+1$ and
$$B(i,j+1,k,l)=B(i,j+1,k,l)+C(i)\frac{\Delta}{\sqrt{\Delta^T\Delta}}$$

iv. Calculate $J(I,j+1,k,l)$ again.

v. Else, m=$N_s$, end of while statement.

h) Go for next bacterium. End of for statement.

6. If $j<N_c$ go to step 3.
7. Reproduction:

a) For each bacterium, let $J^i_{health}=sum\{J_{sw}(i,j,k,l)$ s.t. $j=1,\ldots,N_c\}$. Sort bacteria in order of ascending cost $J_{health}$(higher cost means lower health).

b) Half of the bacteria with highest $J_{health}$ die and the other half will split and the copies are placed in the same place as their parent.

8. If $k<N_{re}$ go to 2.
9. Elimination and Dispersal:

Eliminate and disperse each bacterium with $P_{ed}$ probability. To do so, if one eliminates a bacterium, simply disperse it to a random location in the feasible space.

Figure 2 illustrates the BF algorithm. This should be noted that in the implementation of this algorithm in the defined OPF problem, cost function is actually -µD calculated in equation (11). So, as this algorithm tries to minimize this cost function, equation (12) is being approached.

TABLE. 1.
PARAMETERS OF BACTERIA FORAGING ALGORITHM

| Parameter | Value | Description |
|---|---|---|
| $N_b$ | 100 | Number of Bacteria |
| $N_v$ | 18 | Number of variables |
| $N_s$ | 4 | Limit of swimming length |
| $N_c$ | 15 | Number of chemotaxis iterations |
| $N_{re}$ | 2 | Number of reproduction iterations |
| $N_{ed}$ | 2 | Number of elimination and dispersal iterations |
| $P_{ed}$ | 0.03 | Probability of elimination and dispersal |
| B(i,j,k,l) | Random values within feasible space | Vector of i*th* bacterium in j*th* reproduction step of the k*th* chemotaxis step of the l*th* elimination and dispersal step |
| C(s) | (Length of feasible space of s*th* variable)/Nb | Size of tumble and swimming of s*th* variable |

## 5. SIMULATION RESULTS

To evaluate the proposed algorithm, BFA is applied to IEEE 30-bus power system. The topology and data of this system can be found in [38] or can be obtained from the authors.

### 5.1. Experimental Setup

Conventional particle swarm optimization (CPSO) is applied and compare with BFA with regard to the performance and compatibility in OPF problem. The parameters of these algorithms are depicted in table 2. The algorithms have been run for 50 independent times. The maximum number of iterations in each algorithm is 100. The population size of PSO is chosen 95.

MATLAB 7.6 software is used to simulate these algorithms with a Pentium IV E5200 PC with a 2 gigabyte RAM.

TABLE 2.
PARAMETERS OF APPLIED ALGORITHMS

| **PSO Parameters** | CPSO |
|---|---|
| Inertia Weight (w) | 1 |
| Learning Factor $c_1$ | 2 |
| Learning Factor $c_2$ | 2 |

TABLE 3.
VARIABLE LIMITS OF IEEE 30-BUS POWER SYSTEM (P.U.)

| Limits of Voltages | | | | | | |
|---|---|---|---|---|---|---|
| $V_G^{min}$ | | | $V_G^{max}$ | $V_L^{min}$ | | $V_L^{max}$ |
| 0.95 | | | 1.1 | 0.95 | | 1.1 |
| Limits of Tap Setting and Reactive Power Sources | | | | | | |
| $T_R^{min}$ | | | $T_R^{max}$ | $Q_C^{min}$ | | $Q_C^{max}$ |
| 0.9 | | | 1.1 | 0 | | 0.36 |
| Limits of Reactive Power of Generators | | | | | | |
| Bus | 1 | 2 | 5 | 8 | 11 | 13 |
| $Q_G^{min}$ | -0.298 | -0.24 | -0.3 | -0.265 | -0.075 | -0.078 |
| $Q_G^{max}$ | 0.596 | 0.48 | 0.6 | 0.53 | 0.15 | 0.155 |

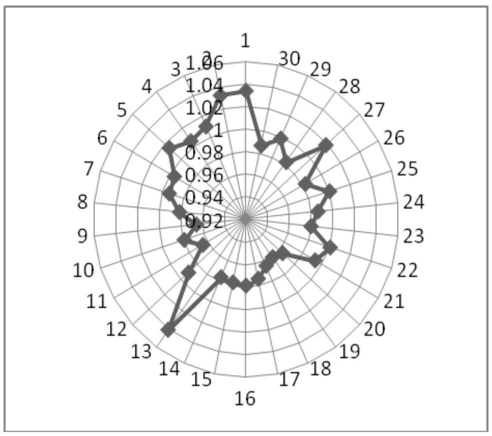


Figure 3. Bus Voltages in p.u.

**5.2. IEEE 30-bus**

The IEEE 30-bus system consists of 48 lines, 6 generators and 2 capacitor banks [38]. There are 4 tap setting transformers installed. Except 6 PV buses, all other buses are PQ buses. The control variable vector includes 6 generator voltages, 4 transformer taps and 3 capacitor banks. Table 3 shows the variable bounds. As mentioned before, the transformer taps and capacitor banks reactive power are discrete variables with the step size of 0.01 p.u. Table 4 illustrates the best OPF results through 50 runs for two algorithms. As this table shows, BFA has lead to lower fuel cost and emission and lower power losses and an acceptable voltage deviation. Hence, it is shown that BFA leads to better results, in comparison with the other algorithm. To demonstrate the results perfectly, the final values of 30 bus voltages and the final reactive power values of six generators are drawn in figures 3 and 4 respectively. It can be observed that all boundary conditions for the variables have been met. The fitness value (fuzzy index) versus the number of iterations is also plotted for two algorithms in figure 5. In this figures BFA results in better convergence than the other algorithm.

Due to random property of the heuristic algorithms in initial solutions, the more trials with diverse initial vectors are generated the more trust-worthy results will be obtained. The performance of the employed algorithms from this viewpoint is shown in table 5 after 50 independent runs.

TABLE 4.
THE BEST OPF RESULTS THROUGH 50 RUNS FOR TWO ALGORITHMS (P.U.)

| Variable | CPSO | BFA |
|---|---|---|
| $P_{G1}$ | 34.24424849 | 75.961549547 |
| $P_{G2}$ | 45.03679624 | 54.462830670 |
| $P_{G5}$ | 0 | 22.329767252 |
| $P_{G8}$ | 73.826053450 | 50.504520809 |
| $P_{G11}$ | 0.0528203963 | 17.613254911 |
| $P_{G13}$ | 27.678512390 | 0.66671036114 |
| $V_{G1}$ | 1.0378273788 | 1.016711395 |
| $V_{G2}$ | 1.0380426076 | 1.009083350 |
| $V_{G5}$ | 1.0087524718 | 0.998381162 |
| $V_{G8}$ | 1.0422658485 | 1.033933378 |
| $V_{G11}$ | 1.0169440126 | 1.018480008 |
| $V_{G13}$ | 1.0651053439 | 1.053041589 |
| $Q_5$ | 19 | 17 |
| $Q_{24}$ | 4 | 1 |
| $T_{R(6-9)}$ | 1.01 | 0.91 |
| $T_{R(6-10)}$ | 1.07 | 1.01 |
| $T_{R(4-12)}$ | 0.99 | 1.04 |
| $T_{R(28-27)}$ | 1.06 | 1.08 |
| Convergence Time | 389.4641975 | 378.32112 |
| Fuel Cost | 855.738245 | 833.5595574 |
| Fuel Emission | 433.745208 | 424.5148646 |
| Power Losses | 3.388399241 | 3.381690518 |
| Volt Deviation | 0.227762066 | 0.071559343 |
| Fuzzy Index | 0.8259762340 | 0.838307019 |

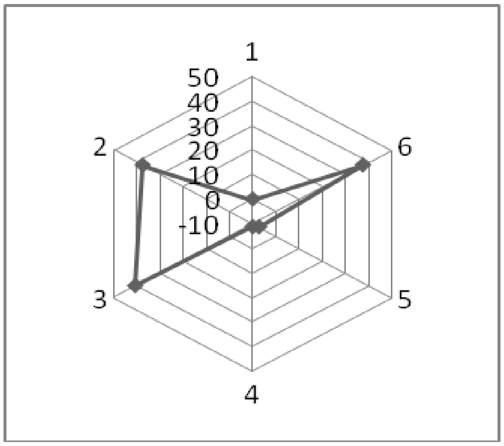


Figure 4. Reactive power of generators.

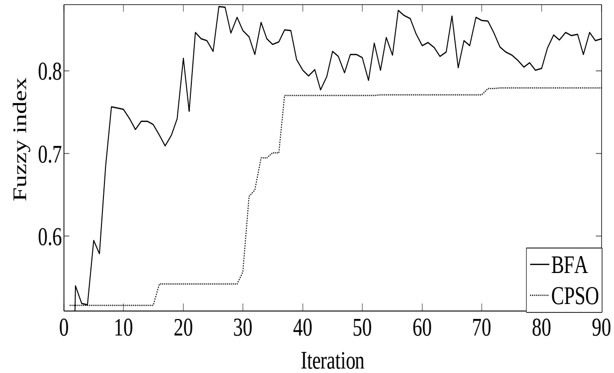


Fig.ure 5. Iterative convergence of different algorithms

## CONCLUSION

In this paper, a multi-objective optimal power flow was formulated. The problem was solved using a proposed multi-objective BFA. Since this algorithm has never been applied in this problem, this paper shows its capability. Then, to handle the multi-objective problem; fuzzy strategy is embedded into the optimization algorithm. . A pseudo goal function derived on the basis of the fuzzy sets theory gives a global performance index of the problem, eliminating the use of weighing coefficients or penalty terms. Four objective functions including cost and emission of generator's fuel, network losses and the voltage deviation of PQ buses are considered simultaneously to perform the best possible dispatch. When this multi-objective technique converted all four objective functions and the constraints into a single objective function, BFA will solved the mixed-integer optimization. Then this single-objective case was simulated using the standard IEEE-30 bus test system. Comparison of case study results with conventional particle swarm optimization (CPSO) showed that the proposed BFA has shown better result and fast convergence in solving the 18 variable problems with regard to solution quality.

Thus, this study shows that BFA can be a serious competitor beside the rest of EA algorithms in OPF problems.

TABLE 5.
COMPARISON OF OPTIMIZATION RESULTS IN THE IEEE 30-BUS

| Compared item | CPSO | BFA |
|---|---|---|
| Worst Fitness | 0.432559349 | 0.796367253 |
| Best Fitness | 0.825976234 | 0.838307019 |
| Mean Fitness | 0.698407597 | 0.818768824 |

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