A hybrid Approach for economic power dispatch

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Abstract: In this paper, a novel hybrid optimization algorithm, which combines a firefly algorithms and Artificial Bee Colony algorithm (FFA- ABC), is proposed for solving the economic power dispatch (EPD) problem. The hybrid algorithm is structured with two stages. The first stage uses the search by firefly algorithm (FFA) and second stage is a search with Artificial Bee Colony algorithm (ABC). The hybrid algorithm involves two level of optimization, namely global search by the ABC and local search by the FFA, which cooperates in a global process of optimization. It can provide more robust convergence. The proposed method is tested in standard IEEE 30 bus and IEEE 57 bus test systems. Numerical results illustrate the feasibility and potential of the proposed hybrid algorithm.

Key-words: Economic power dispatch (EPD), Artificial Bee colony Algorithm, Firefly algorithm, hybrid method.

1 Introduction

The economic power dispatch (EPD) problem has been one of the most widely studied subjects in the power system community since Carpentier first published the concept in 1962 [1]. The EPD problem is a large-scale highly constrained nonlinear non-convex optimization problem [2]. To solve it, a number of conventional optimization techniques such as nonlinear programming (NLP) [3], quadratic programming (QP) [4], linear programming (LP) [5], and interior point methods [6], Newton-based method [7], mixed integer programming[8], dynamic programming [9], branch and bound [10] have been applied. All of these mathematical methods are fundamentally based on the convexity of objective function to find the global minimum. However, the EPD problem has the characteristics of high nonlinearity and nonconvexity.

Applications of conventional optimization techniques such as the gradient-based algorithms are not good enough to solve this problem. Because it depends on the existence of the first and the second derivatives of the objective function and on the well computing of these derivative in large search space.

Therefore, conventional methods based on mathematical technique cannot give a guarantee to find the global optimum. In addition, the performance of these traditional approaches also depends on the starting points and is likely to converge to local minimum or even diverge.

Recently, many attempts to overcome the limitations of the mathematical programming approaches have been investigated such as meta-heuristic optimization methods, for example tabu search(TS) [11], simulated annealing (SA) [12], genetic algorithms [13][14], Evolutionary Programming (EP) [15], artificial neural networks [16][17], particle swarm [18][19], Ant Colony optimization (ACO) [20][21], harmony search algorithm [22]and cooperative evolutive concept learning [23].

Their applications to global optimization problems become attractive because they have better global search abilities over conventional optimization algorithms. The Meta-heuristic techniques seem to be promising and evolving, and have come to be the most widely used tools for solving EPD.

These minimization problems the meta-heuristic methods allow to find solutions closer to the optimum but with high cost in time.

In this regards to solve this problem i.e. improve results and convergence time, we have developed a new hybrid method (FAA-ABC) based the firefly algorithm which was developed by Xin-She Yang at Cambridge University in 2008 and the artificial Bee colony algorithm (ABC) algorithm was proposed by Karaboga in 2005 for solving numerical optimization problems.

Contrary to the most meta-heuristic algorithms, the FFA algorithm has a very great ability to search solutions with a fast speed to converge,

The method is tested on two electrical networks IEEE 30 bus and IEEE57 bus. Simulation results confirm the advantage of computation rapidity and solution accuracy of the proposed method. These results show great promise.

The rest of this paper is organized as follows. Section 2 considers an Economic power dispatch (EPD) formulation and the optimization under equality and inequality constraints. Section 3 discusses an explanation of the Firefly Algorithm (FFA). The Particle Swarm Optimization method is explained in Section 4. Section 5 discusses Artificial Bee colony algorithm. The approach FFA-ABC is presented in section 6. The paper ends with conclusions in Section 7.

2 Economic power dispatch (EPD)

The goal of conventional EPD problem is to solve an optimal allocation of generating powers in a power system [24].

The power balance constraint and the generating power constraints for all units should be satisfied. In other words, the EPD problem is to find the optimal combination of power generations which minimize the total fuel cost while satisfying the power balance equality constraint and several inequality constraints on the system [25].

The total fuel cost function is formulated as follows:

$$f(P_G) = \sum_{i=1}^{NG} f_i(P_{Gi}) \tag{1}$$

$$f_i(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i \tag{2}$$

Where $f(P_G)$, is the total production cost in \$/hr;

$f_i(P_{Gi})$ is the fuel cost function of unit i in \$/hr;

a_i, b_i, c_i are the fuel cost coefficients of unit i;

P_{Gi} is the real power output of unit i in MW;

In minimizing total fuel cost (see Figure. 1) the following constraints should be satisfied.

2.1 Active Power Balance equation

For power balance an equality constraint should be satisfied. The generated power should be the same as total load demand added to the total line losses. It is represented as follows:

$$\sum_{i=1}^{NG} P_{Gi} = \sum_{j=1}^{ND} P_{Dj} + P_L \tag{3}$$

$\sum_{j=1}^{ND} P_{Dj}$ is the total system demand;

$\sum_{i=1}^{NG} P_{Gi}$ is the total system production;

P_L is the total transmission loss of the system in MW;

NG is the number of generator units in the system;

ND is number of loads.

2.2 Active Power Generation limits

Generation power of each generator should be laid between maximum and minimum limits. There are following inequality constraints for each generator

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \tag{4}$$

$P_{Gi}^{\min}$, $P_{Gi}^{\max}$ are the minimum and maximum generation limits of the real power of unit i.
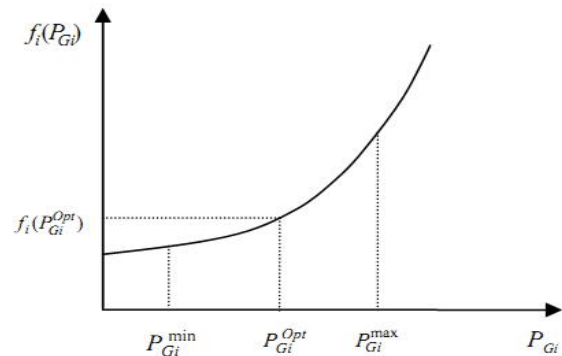

Fig.1 Fuel cost curve of thermal generator.

The exact value of the system losses can be determined by means of a power flow solution. The most popular approach for finding an approximate value of the losses is by way of Kron's loss formula as given in (5), which represents the losses as a function of the output level of the system generators.

$$P_L = \sum_i \sum_j P_{Gi} B_{ij} P_{Gj} \tag{5}$$

Where B_{ij} is the transmission loss coefficient, P_{Gi}, P_{Gj} the power generation of ith and j[th] units.

3 Firefly algorithm

Fireflies (lightning bugs) use their bioluminescence to attract mates or prey. They live in moist places under debris on the ground, others beneath bark and decaying vegetation.

Firefly Algorithm (FFA) was developed by Xin-She Yang at Cambridge University in 2007. It uses the following three idealized rules:

1) Each firefly attracts all the other fireflies with weaker flashes [26].All fireflies are unisex so that a firefly will be attracted to other fireflies regardless of their sex.

2) Attractiveness is proportional to their brightness; thus for any two flashing fireflies the less bright will move towards the brighter one. The attractiveness is proportional to the brightness and they both decrease as their distance increases. If there is no brighter firefly than a particular one it will move randomly.

3) The brightness of a firefly is affected or determined by the landscape of the objective function.

For a maximization problem the brightness can simply be proportional to the value of the objective function. Other forms of brightness can be defined in a similar way to the fitness function in genetic algorithms based on these three rules.

3.1 Attractiveness

In the firefly algorithm there are two important issues: the variation of light intensity and the formulation of the attractiveness. For simplicity, we can always assume that the attractiveness of a firefly is determined by its brightness which in turn is associated with the encoded objective function [27].

In the simplest case for maximum optimization problems, the brightness I of a firefly at a particular location x can be chosen as $I(x)$ corresponding to $f(x)$. However, the attractiveness β is relative; it should be seen in the eyes of the beholder or judged by the other fireflies [24]. Thus, it will vary with the distance r_{ij} between firefly i and firefly j. In addition, light intensity decreases with the distance from its source and light is also absorbed in the media so we should allow the attractiveness to vary with the degree of absorption. In the simplest form, the light intensity $I(r)$ varies according to the inverse square law $I(r) = I_s / r^2$

Where I_s is the intensity at the source.

For a given medium with a fixed light absorption coefficient, the light intensity I varies with the distance r [28].

That is $I = I_0 e^{-\gamma r}$, where I_0 is the original light intensity. In order to avoid the singularity at

$r = 0$ in the expression $I(r) = I_s / r^2$ the combined effect of both the inverse square law and absorption can be approximated using the following Gaussian form:

$$I(r) = I_0 e^{-\gamma r^2} \tag{6}$$

Sometimes we may need a function which decreases monotonically at a slower rate. In this case we can use the following approximation:

$$I(r) = \frac{1}{1 + e r^2} I_0 e^{-\gamma r^2} \tag{7}$$

At a shorter distance, the above two forms are essentially the same. This is because the series expansions about $r = 0$ have the form:

$$e^{-\gamma r^2} \approx 1 - \gamma r^2 + .., \frac{1}{1 + \gamma r^2} \approx 1 - \gamma r^2 + .., \tag{8}$$

And are equivalent to each other up to the order of $0(r^3)$.

Since a firefly's attractiveness is proportional to the light intensity seen by adjacent fireflies, we can now define the attractiveness β of a firefly by:

$$\beta(r) = \beta_0 e^{-\gamma r^2} \tag{9}$$

Where β_0 is the attractiveness at $r = 0$. As it is often faster to calculate $1/ (1 + r^2)$ than an exponential function, the above expression, if necessary, can conveniently be replaced by $\beta = \dfrac{\beta_0}{1 + e r^2}$. Equation

(9) defines a characteristic distance $\Gamma = \dfrac{1}{\sqrt{\gamma}}$ over which the attractiveness changes significantly from β_0 to $\beta_0 e^{-1}$.

In the implementation, the actual form of attractiveness function $\beta(r)$ can be any monotonically decreasing function such as the following generalized form:

$$\beta(r) = \beta_0 e^{-\gamma r^m} \text{ with } m \geq 1 \tag{10}$$

For a fixed γ, the characteristic length becomes

$\Gamma = \gamma^{-1/m} \to 1$ as $m \to \infty$.

Conversely, for a given length scale Γ in an optimization problem, the parameter γ can be used as a typical initial value. That is

$\gamma = \dfrac{1}{\Gamma^m}$.

3.2 Distance and Movement

The distance between any two fireflies i and j at x_i and x_j is the Cartesian distance given by [29] as follows:

$$r_{ij} = |x_i - x_j| = \sqrt{\sum_{k}^{d}(x_{i,k} - x_{j,k})^2} \tag{11}$$

Where x_{ik} is the kth component of the spatial coordinate x_i of ith firefly as shown in fig.2 the movement of a firefly i is attracted to another more attractive firefly j is determined by

$$x_{i+1} = x_i + \beta_0 e^{-\lambda r_{ij}^2}(x_j - x_i) + \alpha\left(rand - \frac{1}{2}\right) \tag{12}$$

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 the random movement of a firefly in case there are not any brighter ones.

The coefficient α is a randomization parameter determined by the problem of interest, while rand is a random number generator uniformly distributed in the space [0, 1]. As we will see in this implementation of the algorithm, we will use β_0 =0.1, $\alpha \in$ [0, 1] and the attractiveness or absorption coefficient γ= 1.0 which guarantees a quick convergence of the algorithm to the optimal solution [30].

4 Particle swarm optimization method

The particle swarm optimization works by adjusting trajectories through manipulation of each coordinate of a particle. Let x_i and v_i denote the positions and the corresponding flight speed (velocity) of the particle i in a continuous search space, respectively.

The particles are manipulated according to the following equations [31, 32 and 33].

$$v_i^{(t+1)} = wv_i^{(t)} + c_1 r_1(x_{gbest}^{(t)} - x_i^{(t)}) + c_2 r_2(x_{ipbest}^{(t)} - x_i^{(t)}) \tag{13}$$

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \tag{14}$$

Where:
t : pointer of iterations (generations).
w : inertia weight factor.
c_1, c_2 : acceleration constant.
r_1, r_2 : uniform random value in the range (0,1).
$v_i^{(t)}$: velocity of particle i at iteration t.
$x_i^{(t)}$: current position of particle i at iteration t.
$x_{ipbest}^{(t)}$: previous best position of particle i at iteration t.
$x_{gbest}^{(t)}$: best position among all individuals in the population at iteration t.
$v_i^{(t+1)}$: new velocity of particle i.
$x_i^{(t+1)}$: new position of particle i.

Algorithm
1. Initialize the population - positions and velocities
2. Evaluate the fitness of the individual particle (*pbest*)
3. Keep track of the individuals highest fitness (*gbest*)
4. Modify velocities based on *pbest* and *gbest* position
5. Update he particles position
6. Terminate if the condition is met
7. Go to Step 2

5 Artificial Bee Colony algorithm

Artificial Bee Colony (ABC) algorithm, proposed by Karaboga [34] for optimizing numerical problems in, simulates the intelligent foraging behavior of honey bee swarms. An idea based on honey bee swarm for numerical optimization. In ABC algorithm, the colony of artificial bees contains three groups of bees: employed bees, unemployed bees (onlookers and scouts) The scout bees randomly search the enviroment surriounding the hive for new food sources and this bevavior is a kind of fluctuations which is vital for self-organization.

The outlookers waiting in the hive find a food source by means of information presented by employed foragers.

The mean number of scouts is about 5 –10% of the foragers. In ABC, first half of the colony consists of employed artificial bees and the second half constitutes the artificial onlookers. The employed bee whose food source has been exhausted becomes a scout bee[34].

In ABC algorithm, the position of a food source represents a possible solution to the optimization problem and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution. The number of the employed bees is equal to the number of food sources, each of which also represents a site, being exploited at the moment or to the number of solutions in the population[35].

The main steps of the algorithm are given below:

• Initialize.

• REPEAT.

(a) Place the employed bees on the food sources in the memory;

(b) Place the onlooker bees on the food sources in the memory;

(c) Send the scouts to the search area for discovering new food sources.

• UNTIL (requirements are met).

In the ABC algorithm, each cycle of the search consists of three steps: sending the employed bees onto the food sources and then measuring their nectar amounts; selecting of the food sources by the onlookers after sharing the information of employed bees and determining the nectar amount of the foods; determining the scout bees and then sending them onto possible food sources.

1) Initialize the population of solutions

$$x_i = \left(x_{ij} \right)$$

2) Evaluate the population

3) cycle=1

4) repeat

5) Produce new solutions (food source positions) v_i in the neighbourhood of x_i for the employed bees; for example using the following formula.

$$v_{ij} = x_{ij} + \varphi_{ij} \left(x_{ij} \quad x_{kj} \right) \tag{15}$$

6) Apply the greedy selection process between v_i and x_i.

7) Calculate the probability values pi for the solution x_i by means of their fitness values f_i. For example, using the following equation.

$$P_i = \frac{f_i}{\sum_{i=1}^{SN} f_i} \tag{16}$$

For the minimization problem, the fitness value might be calculated as follows.

$$f_i = \begin{cases} \dfrac{1}{1+F_i} & if \quad F_i \geq 0 \\ 1+abs(F_i) & if \quad F_i \; 0 \end{cases} \tag{17}$$

Where : F_i is the cost value of the objective function.

8) Produce new solutions (new positions) v_i for the onlookers from the solutions x_i, selected depending on pi and evaluate them.

9) Apply the greedy selection process between v_i and x_i.

10) Determine the abandoned solution (source) x_i, if exists, and replace it with a new randomly produced solution x_i for the scout. The following definition might be used for this purpose.

$$x_{ij} = x_{\min j} + rand(0,1) \times \left(x_{\max j} \quad x_{\min j} \right) \tag{18}$$

where x_{minj} is the lower bound of the parameter j and x_{maxj} is he upper bound of the parameter j.

11) Memorize the best food source position (solution) achieved so far

12) cycle=cycle+1

13) until (cycle= Maximum Cycle Number (MCN))

6 Firefly algorithm-Artificial Bee Colony algorithm (FFA-ABC)

We have noticed that the meta-heuristic methods are very efficient for the search of global solution for complex problems better than deterministic methods.

However their disadvantage is the time of convergence which is due the high number of the agents and iterations. To solve this problem we have combined two meta-heuristic methods, the firefly and the artificial colony algorithm with a lower number of bees and fireflies as possible.

This paper proposes a hybrid method which has two search stages. The first stage is a search by firefly algorithm (FFA) and second stage is a search with Artificial Bee Colony algorithm (ABC). The Figures.2,3,4 and 5 show the explanation of computation procedure of hybrid method and its concept.
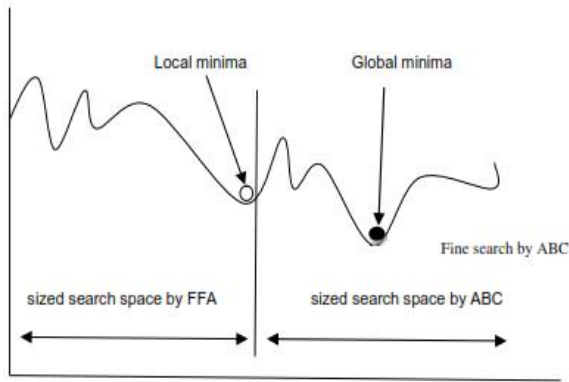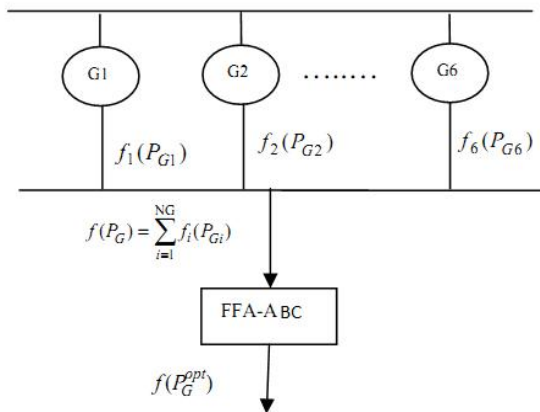
Fig.2 Concept of Hybrid Method

Fig.3 Global optimization of all the generators of the IEEE 30 system
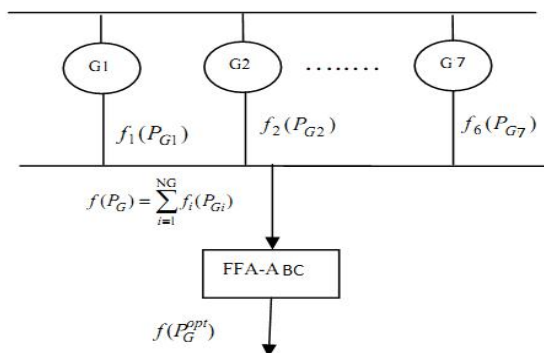

Fig.4 Global optimization of all the 7generators of the IEEE 57 bus system

Fig.5 The pseudo code of FFA-ABC

7 Simulation results.

The proposed method has been tested on two electrical networks IEEE 30-bus and IEEE 57 bus.

7.1 The IEEE 30 bus.

The system consists of 41 lines, 6 generators, 4 Tap-changing transformers and shunt capacitor banks located at 9 buses

The table 1 shows the technical and economic parameters of the ten generators of the IEEE 30-bus system (Show in Figure 6).Total load demand of the system is 283.4000 MW

7.2 The IEEE 57 bus.

The IEEE 57 bus system has 80 transmission circuits. The single-line diagram of this system is shown in Fig. 7 and the detailed data are given in [9]. The values of fuel cost coefficients are given in Table.2, Total load demand of the system is 1250.8 (MW), and 7 generators should satisfy this load demand economically.
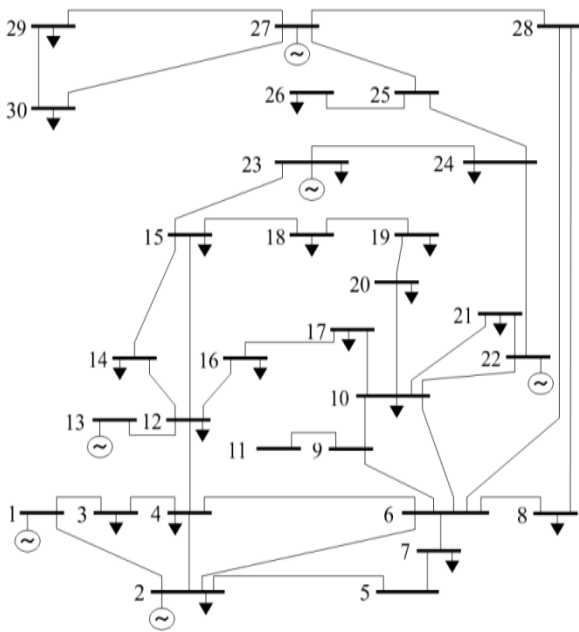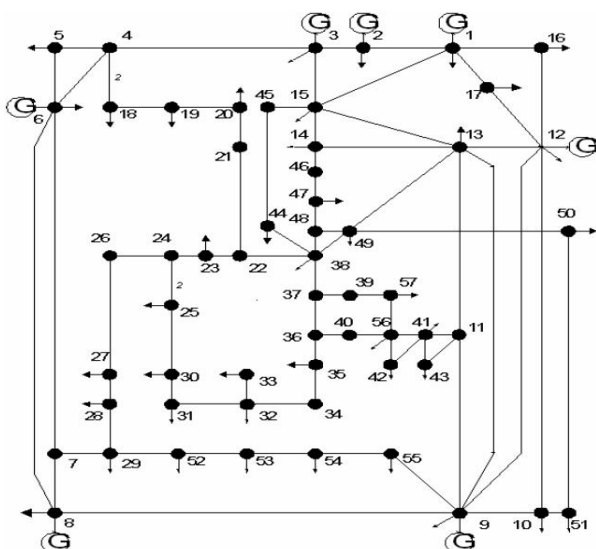
Fig.6 One line diagram of IEEE 30 bus system

Fig.7 One line diagram of IEEE 57 bus system

Table.4 presents the results of each method individually respectively the ABC and FFA methods

as well as the results of the hybrid approach FFA-ABC applied to a network with 30 nodes with a power demand 283.40MW and constant losses of 9.459 MW.

Table.1 Generators parameters of the IEEE 30 Bus

Bus	p_{Gi}^{min} (MW)	p_{Gi}^{max} (MW)	Cost coefficients		
			a_i	b_i	c_i
P_{G1}	50	200	0.00375	2.00	0.00
P_{G2}	20	80	0.01750	1.75	0.00
P_{G5}	15	50	0.06250	1.00	0.00
P_{G8}	10	35	0.00834	3.25	0.00
P_{G11}	10	30	0.02500	3.00	0.00
P_{G13}	12	40	0.02500	3.00	0.00

Table.2 Generators parameters of the IEEE 57 Bus

Bus	p_{Gi}^{min} (MW)	p_{Gi}^{max} (MW)	Cost coefficients		
			a_i	b_i	c_i
P_{G1}	0.00	575.88	0.01	0.30	0.20
P_{G2}	0.00	100	0.01	0.30	0.20
P_{G3}	0.00	140	0.01	0.30	0.20
P_{G6}	0.00	100	0.01	0.30	0.20
P_{G8}	0.00	550	0.01	0.30	0.20
P_{G9}	0.00	100	0.01	0.30	0.20
P_{G12}	0.00	410	0.01	0.30	0.20

Table.3 FFA-ABC method parameters

Parameter	Setting
Number of iterations FFA-ABC	200
the population size for firefly(n)	10
the light absorption coefficient(γ)	1.0
a randomization parameter of FFA(α)	0.4
The attractiveness coefficient of FFA(β_0)	1.0
Colony size (employed bees + onlooker bees)	30
Food sources =	15

Table.4 Optimization results of FFA-ABC approach for IEEE 30 bus

Bus	MDEOPF [37]	PSO	ABC	FFA	FFA-ABC
P_{G1}	175.974	178.061	178.061	178.710	190.382
P_{G2}	48.884	54.056	54.056	49.017	47.800
P_{G5}	21.510	19.836	19.836	22.151	19.399
P_{G8}	22.240	14.890	14.890	14.112	11.862
P_{G11}	12.251	12.427	12.427	13.587	15.262
P_{G13}	12.000	13.129	13.129	14.693	14.024
P_L	9.459	9.459	9.459	9.459	9.459
t(s)	23.070	14.961	13.768	12.373	10.219
Cost ($/hr)	**802.376**	**801.105**	**801.105**	**801.588**	**799.270**

Table.5. Comparison of different methods for IEEE 57 bus system

Bus	$M_{ATPOWER}$OPF [38]	GAOPF [38]	$GAM_{ATPOWER}$OPF [38]	PSO	FFA-ABC
P_{G1}	265.330	277.127	277.149	311.212	301.890
P_{G2}	100.000	100.000	100.000	97.232	97.468
P_{G3}	140.000	140.000	140.000	122.835	139.980
P_{G6}	100.000	100.000	100.000	98.598	92.183
P_{G8}	276.970	277.260	277.282	269.168	236.501
P_{G9}	100.000	100.000	100.000	99.965	99.115
P_{G12}	287.560	275.403	275.403	266.826	301.582
P_L	16.060	19.06	19.060	19.060	19.060
Cost ($/hr)	**3176.390**	**3175.579**	**3173.982**	**3156.684**	**3149.614**

Tables 4 and 5 illustrate the results of the application of the methods ABC, FFA, PSO and FFA-ABC as well as the results of other researchers [37]-[38] with two electrical networks. These results clearly show the effectiveness and performance of the FFA-ABC over other methods either in terms of function cost value or in terms of convergence time as shown in Figures.8,9,10 and 11.
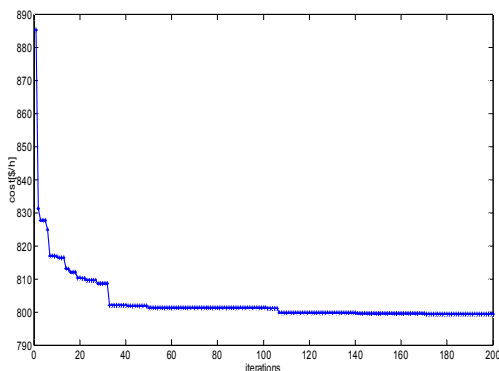

Fig.8 The function cost values in different iterations for FFA-ABC method (IEEE 30 BUS)
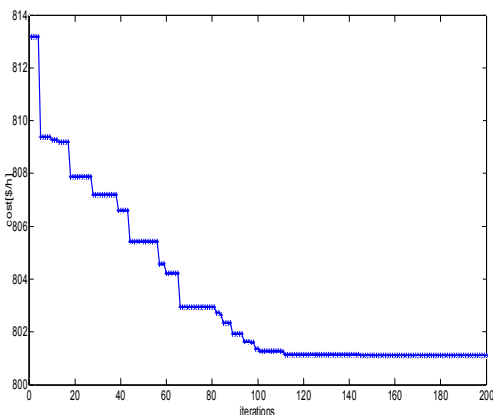

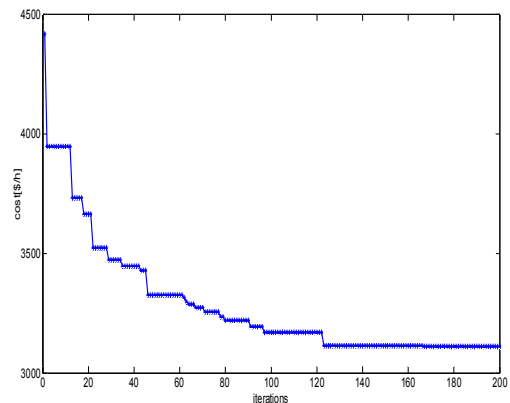Fig.9 The function cost values in different iterations for ABC method (IEEE 30 BUS)

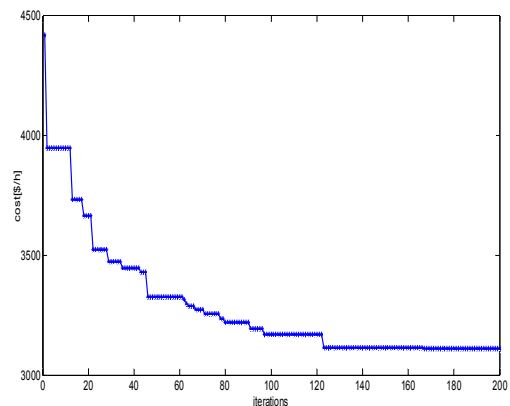Fig.10 The function cost values in different iterations for PSO method (IEEE 57bus)

Fig.11 The function cost values in different iterations for FFA-ABC method (IEEE 57bus)

8 Conclusion

This paper presents a methodology for solving EPD including active power dispatch using two Meta heuristic methods based on firefly and artificial Bee colony algorithm. The method developed was tested on the IEEE 30 bus and IEEE 57 bus. The case studies have shown that method is robust and can provide an optimal solution with fast computation time and a small number of iterations.

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