A novel Hybrid FFA-ACO Algorithm for Economic Power Dispatch

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Abstract: In this article, I developed a practical combination strategy for two evolutionary algorithms; a firefly algorithm and Ant Colony Optimization (FFA- ACO) which inherited the superiority of the two algorithms for solving the economic power dispatch (EPD) problem. ACO has strong and easy to combine with other methods in optimization and the FFA algorithm has a very great ability to search solutions with a fast speed to converge, contrary to the most meta-heuristic algorithms. The hybrid approach involves two level of optimization, namely global search by the ACO and local search by the FFA, which cooperates in a global process of optimization. It can provide more robust convergence. This method was tested on the modified IEEE 30 bus test system. The outcomes are compared with many other methods like swarm optimization (PSO), Tabu Search (TS), improved evolutionary programming (IEP), differential evolution (DE), evolutionary programming (EP) and non-linear programming (NLP). The proposed method is found to be computationally faster, robust and superior.

Keywords: Economic power dispatch (EPD), Ant colony Optimization, Firefly algorithm, hybrid method.

1. INTRODUCTION

To cope with the increasing demand for electric power, the electric power industry has witnessed significant changes i.e. deregulated electricity markets. These competitive markets reduce costs. The increased penetration of non-dispatchable renewable sources, such as wind and solar, adds another degree of complexity to the scheduling of economic power dispatch. It becomes even more complex when more than one objective function is considered with various types of practical generators constraints. All these factors contribute to the increasing need for fast and reliable optimization methods, tools and software that can address both security and economic issues simultaneously in support of power system operation and control.

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 (Carpentier, 1962). the EPD problem is a large-scale highly constrained nonlinear non-convex optimization problem (Vanderbei *et al.,* 1999). To solve it, a number of conventional optimization techniques such as nonlinear programming (NLP) (Bottero *et al.,* 1982), quadratic programming (QP) (Reid *et al.,* 1973), linear programming (LP) (Stott *et al.,* 1978), and interior point methods (Momoh *et al.,* 1999), Newton-based method (Sun *et al.,* 1984; Santos *et al.,* 998), mixed integer programming (Bahiense *et al.,* 2001), dynamic programming (Dusonchet *et al.,* 1973), branch and bound (Haffner *et al.,* 2000) 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 non-convexivity.

Applications of conventional optimisation 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 computing of these derivatives in large search space.

The 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) (Glover *et al.,* 1986; Abido *et al.,* 2002), simulated annealing (SA) (Kirkpatrick *et al.,* 1983), genetic algorithms (Lai *et al.,* 1997; Petridis *et al.,* 1998; Younes et *al.,* 2007), Evolutionary Programming (EP) (Yuryevich *et al.,* 1999; Younes *et al.,* 2006; Sayah *et al.,* 2008), artificial neural networks (Maghrajabi *et al.,* 1998), particle swarm (Abido *et al.,* 2002; Immanuel *et al.,* 2007; Eslami *et al.,* 2010; Younes *et al.,* 2011), Ant Colony optimization (ACO) (Song *et al.,* 1999, Sum-im *et al.,* 2003; Younes *et al.,* 2009), harmony search algorithm (Fesanghary *et al.,* 2008; Younes *et al.,* 2012), and hybrid artificial intelligent techniques (Younes *et al.,* 2007).

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 of meta-heuristic methods allow solutions to be found closer to the optimum but with high cost in time.

In this regards to solving this problem i.e to improve results and convergence time, I developed a practical combination strategy for two evolutionary algorithms (FFA- ACO) based on the ant colony algorithm (ACO), This was developed by Dorigo M in the early 1990, firefly algorithm which was developed by Xin-She Yang at Cambridge University in 2008.

ACO has robustness and is easy to combine with other methods in optimization but it converges to the optimal solution slowly and has the shortcomings of stagnation that limit the wide application to the various areas. 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 investigation using this approach has been made with consideration to the IEEE 30-bus system.

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 Ant Colony Optimization algorithm. The approach FFA-ACO is presented in section 6. Simulation results and discussions are given in Section 7. The paper ends with conclusions in Section 8.

2. ECONOMIC POWER DISPATCH (EPD)

The goal of conventional EPD problem is to solve an optimal allocation of generating powers in a power system (*Younes et al.,* 2012).

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 (Younes *et al.,* 2006).

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 (Younes.M *et al.,* 2007).

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.

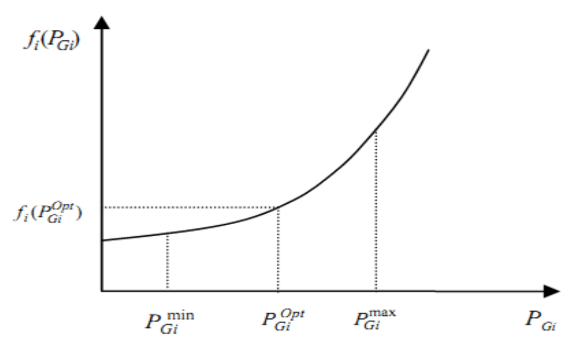

Fig. 1. Fuel cost curve of thermal generator.

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.

$$P_L = \sum_i \sum_j P_{Gi} B_{ij} P_{Gj} \quad (5)$$

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

3. FIREFLY ALGORITHM

Firefly algorithm is a novel meta-heuristic optimization algorithm which was first developed by Xin-She Yang at Cambridge University in 2008. The Firefly Algorithm is a metaheuristic, nature-inspired optimization algorithm which is based on the social flashing behavior of fireflies. It is based on the swarm behavior such as fish, insects or bird schooling in nature. Although the firefly algorithm has many similarities with other algorithms which are based on the so-called swarm intelligence, such as the famous Particle Swarm Optimization (PSO) and Artificial Bee Colony optimization (ABC) , it is indeed much simpler both in concept and implementation. Its main advantage is that it uses mainly real random numbers, and it is based on the global communication among the swarming particles called as fireflies. it has been successfully applied to many engineering optimization problems. Optimization for IIR System Identification (Mehrnoosh *et al.,* 2012), Economic Load Dispatch (Sudhakara *et al.,* 2012), Economic Emissions Load Dispatch Problem (Apostolopoulos *et al.,* 2011), Antenna Design (Basu *et al.,* 2011), Digital Image Compression and Image Processing (Noor *et al.,* 2011).

It uses the following three idealized 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 (Apostolopoulos *et al.,* 2011).

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 tof(x). However, the attractiveness β is relative; it should be seen in the eyes of the beholder or judged by the other fireflies (Yang .X.S, 2010). 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 (Yang .X.S, 2009).

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:

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

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

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

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

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

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:

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

whereβ_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 $\beta = \frac{\beta_0}{1 + er^2}$. Equation (9) defines a characteristic distance $\Gamma = \frac{1}{\sqrt{\gamma}}$ 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:

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

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

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 (Sayadi *M. et al.,* 2010) as follows:

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

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

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

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, α Є [0, 1] and the attractiveness or absorption coefficient γ= 1.0 which guarantees a quick convergence of the algorithm to the optimal solution (Chai-ead et al, 2011).

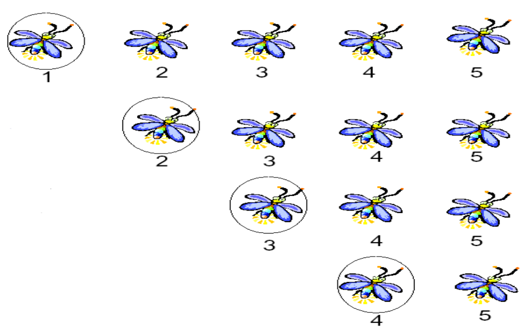

Fig. 2. Displacement of fireflies.

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 (Clerc M *et al.,* 2002; Eberhart *et al.,* 1995; Kennedy *et al.,* 1995).

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

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

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. ANT COLONY OPTIMIZATION

As shown in Figure 3, two ants start from their nest in search of food source at the same time to different directions. One of them chooses the path that turns out to be shorter while the other takes the longer sojourn. The ant moving in the shorter path returns to the nest earlier and the pheromone deposited in this path is obviously more than what is deposited in the longer path. Other ants in the nest thus have high probability of following the shorter route.

Colony Optimization is another powerful technique to solve hard combinatorial optimization problems. In ACO algorithms a finite number of artificial ants work together to search for the best solutions to the optimization problem under consideration. Each ant builds a solution and exchanges its information with other ants indirectly (Nada .M.A, 2009). Although each ant can build a solution, high quality solutions are only found with this cooperation and information exchange (Dorigo *et al.,* 1997).

In ACO algorithms a structural neighbourhood is defined for the given problem. Each ant builds a solution by moving in a sequence trough out the neighbourhood architecture. While building a solution each ant uses two different information sources.

The first source is private information which is the local memory of an ant and the second source is the publicly available pheromone trail together with problem specific heuristic information (Younes *et al.,* 2009).

To build a feasible solution ants keep a tabulated list to keep the previously visited nodes. Publicly available pheromone trail provides knowledge about the decisions of ants from the beginning of the search process. An ant-decision table defined with the functional combination of this pheromone trail and problem specific heuristic values is used to direct the search. Pheromone evaporation strategies are used to avoid stagnation due to large accumulations (Dorigo M, 1992).

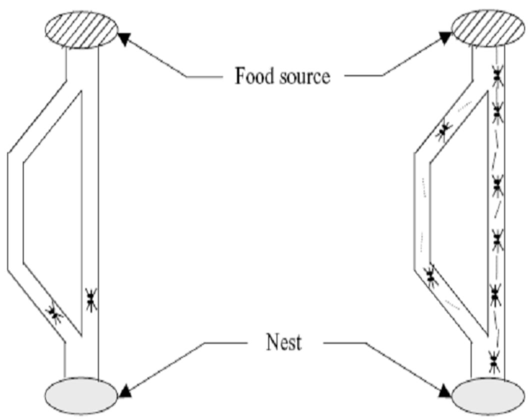

Fig. 3. Movement of Ant algorithm.

5.1 Solution Construction

Is where the artificial ants construct their solutions. This procedure implements a stochastic transition policy which is a function of pheromone trail. It controls the ants' moves to one of the adjacent states allowed in their vicinity by applying this policy. Once the ants have completed their solutions they calculate the quality of their solution, which will be used by the update pheromones procedure (Dorigo et al., 1996).

In ACO there are m artificial ants which are located at m random cities. Each ant applies a stochastic transition policy to decide on its next move.

Therefore, the probability that city j is selected by ant k to be visited after city i could be written as follows:

$$P_{ij}^{k}(t)=\begin{cases}\dfrac{[\tau_{ij}]^{\alpha}\cdot[\eta_{ij}]^{\beta}}{\sum\limits_{l\in N_i^k}[\tau_{il}(t)]^{\alpha}\cdot[\eta_{il}]^{\beta}} & if \quad j \ \in \ N_i^k\end{cases} \tag{15}$$

In the above formula η_{ij} stands for the heuristic value specified according to the problem to be solved. In the Travelling Salesman Problem (TSP) case, η_{ij} is equal to $1/d_{ij}$.

N_i^k is the feasible neighbourhood of ant k at city i and τ_{ij} is the quantity of the pheromone on the path between the city i and j.

α and β are the parameters which is used to set the relative importance of the pheromone trail and the heuristic value. As α approaches 0 the pheromone trails become less important and the ants tend to choose the closest cities and the search becomes very much like a greedy search.

As β approaches 0 heuristic values are ignored and ants consider only the trails when deciding the path to follow. This leads to stagnation at the first good solutions found by the colony.

5.2 Pheromone Update

At the beginning m ants are placed to the n cities randomly.

Then each ant decides the next city to be visited according to the probability P_{ij}^k given by Eq. (15). After n iterations of this process every ant completes a tour. Obviously, the ants with shorter tours should leave more pheromone than those with longer tours. Therefore the trail levels are updated as on a tour each ant leaves pheromone quantity given by $1/L^k$, where L^k the length of its tour respectively. On the other hand, the pheromone will evaporate as the time goes by. Then the updating rule of τ_{ij} could be written as follows:

$$\tau_{ij}(t+1)=\rho\cdot\tau_{ij}(t)+\Delta\tau_{ij} \tag{16}$$

$$\Delta\tau_{ij}=\sum_{k=1}^{m}\Delta\tau_{ij}^{k}\ ;$$

$$\Delta\tau_{ij}^{k}=\begin{cases}\dfrac{1}{L^k}, & \text{If edge(i, j) is solution of ant k,}\\ 0 & \text{otherwise}\end{cases} \tag{17}$$

Where t is the iteration counter, ρ Є [0, 1] the parameter to regulate the reduction of τ_{ij} the total increase of trail level on edge (i, j) and $\Delta\tau_{ij}$ k the increase of trail level on edge (i, j) caused by ant k, respectively.

After the pheromone trail updating process, the next iteration t + 1 will start.

1. Initialize:

Set time:=0 % is time counter

For every edge (i,j) set an initial value $\tau_{ij}(t)=c$ for trail density and $\Delta\tau_{ij}=0$

2. Set t:=0 %s is travel step counter

For k:=1 to m do

Place ant k on a city randomly. Place the city in visited$_k$.

Place the group of the city in tabu$_k$.

3. Repeat until tabu list is full

Set t:=t + 1

For k:=1 to m do

Choose the next city to be visited according to the probability $P_{ij}^{k}(t)$ given by eq (15).

Insert the selected city in visited$_k$.

Insert the group of selected city in tabu$_k$.

4. For k:=1 to m do

Move the k-thant fromvisited$_k$(n) to visited$_k$(1).

Compute the tour length Lktraveled by the k-th ant.

Update the shortest tour found.

For every edge (i, j) do

For k:=1 to l do

Update the pheromone trail density τ_{ij} according to Eqs.

(16)– (17).

Time: =time + 1

5. If (time<TIME_MAX) then

Empty all visitedk and tabu$_k$

Goto Step 2.

Else

Print the shortest tour.

Stop

6. FIREFLY ALGORITHM-ANT COLONY OPTIMIZATION (FFA-ACO)

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 developed a hybrid method with the combination of two algorithms, the firefly algorithm and the Ant Colony Optimisation with a lower number of ants and fireflies as possible, the Figures 4, 5 and 6 show the explanation of computation procedure of hybrid method and its concept.

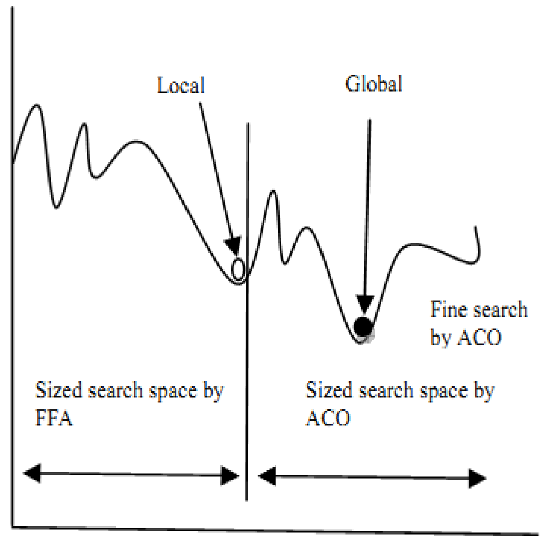

Fig. 4. Concept of Hybrid Method

```
Initialize approach parameters;
Generate the initial population of fireflies or xi (i=1, 2,..., n)
Light Intensity of firefly n is determined by objective
function,In ~ f(x)
While (termination criterion not satisfied)
For i = 1 to n (all n fireflies);
For j=1 to n (n fireflies)
if (Ij > Ii), move firefly i towards j; end if
Attractiveness varies with distance r via Exp[-γr²];
Evaluate new solutions and update light intensity;
End for j;
End for i;
Rank the fireflies and find the current best;
End while;
The best solutions found by FFA are regarded as initial points
for ACO
While (termination criterion not satisfied)
Schedule activities
Ants generation and starting point;
Makes path or step for each ant
Compare response function;
If no improvement of response function then
Communication with best ant response function;
Make path or step from local trap to best ant;
Else
If ant found the better response function then
go to line 15;
Else
Wait for best ant communication;
End if;
End if;
End schedule activities;
End while;
Process results;
End procedure;
```

Fig. 5. The pseudo code of FFA-ACO.

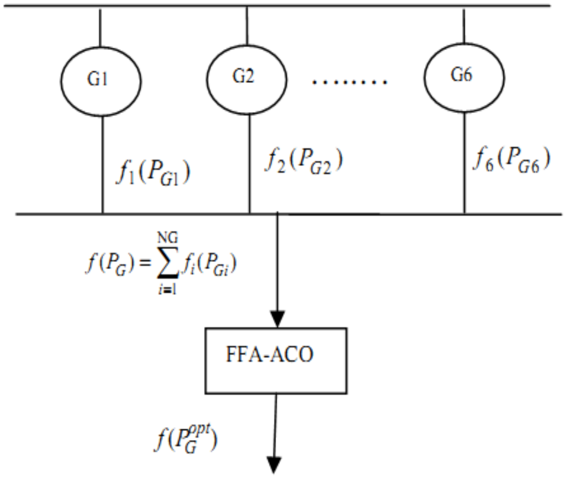

Fig. 6. Global optimization of all the generators of the system.

7. SIMULATION RESULTS

The FFA-ACO approach has been developed using Matlab version 7. It is tested using the modified IEEE 30-bus system (Sayah *et al.,* 2008). . 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 7).

The parameter settings to execute FFA-ACO are given in table 2

Two cases have been considered:
1) The first concerns the minimization of the cost function with constant losses
2) The second the minimization of the cost function with variable loss

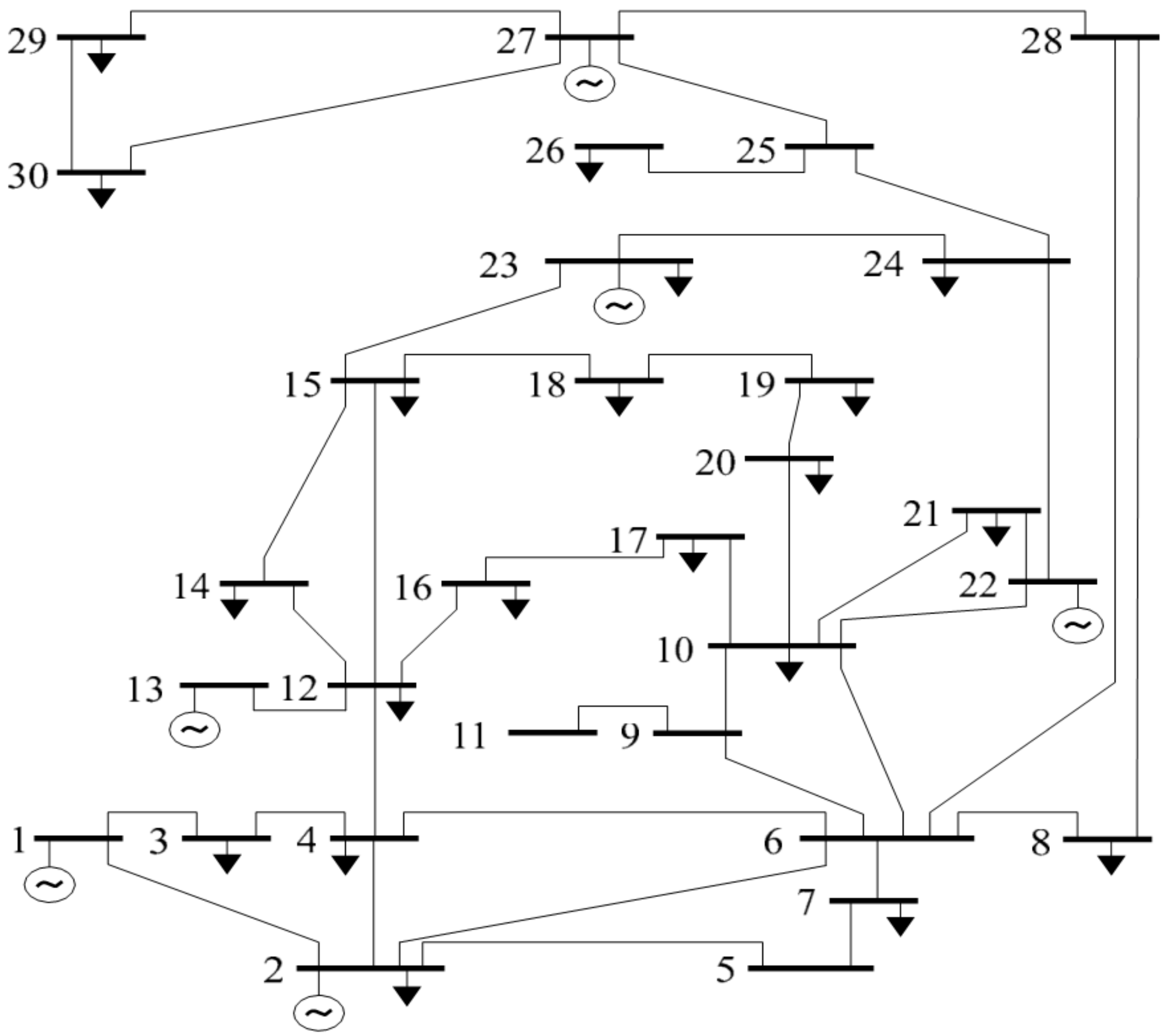

Fig. 7. One line diagram of IEEE 30 bus system.

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. FFA-ACO method parameters.

Parameter	Setting
Number of iterations FFA-ACO	113
the population size for firefly(n)	8
the light absorption coefficient(γ)	1.0
a randomization parameter of FFA(α)	0.4
*T*he attractiveness coefficient of FFA(β_0)	1.0
number of ants (m)	8
Pheromone constant (ρ)	0.5
Impact of pheromone in tour construction (α)	0.5
Impact of objective value in tour construction (β)	5

7.1 Case 1: Minimizing the Function with Constant Losses

Table 3 presents the results of each method individually respectively the ACO and FFA methods as well as the results of the hybrid approach FFA-ACO applied to a network with 30 bus with a power demand 283.40MW and constant losses of 9.459 MW.

Table 3. Optimization results of FFA-ACO approach for case study1

Bus	MDE-OPF [3]	PSO	ACO	FFA	FFA-ACO
P_{G1}	175.974	157.022797	178.3294	178.6412	183.1917
P_{G2}	48.884	41.443507	46.1420	50.3891	50.5993
P_{G5}	21.510	23.564700	22.3608	21.7411	20.2589
P_{G8}	22.240	25.943875	23.8185	16.8022	16.5259
P_{G11}	12.251	21.653973	10.0000	13.1006	10.3440
P_{G13}	12.000	19.447432	12.0000	12.0000	12.0000
P_L	9.459	9.459	9.459	9.459	9.459
t(s)	23.07	16.2569	14.9688	13.8334	10.7292
Cost ($/hr)	802.62	801.774659	801.7739	801.0074	800.788

7.2 Case 2: Minimizing the Cost Function taking into Consideration the Variable Losses

Table 4 presents the results of PSO and the hybrid approach FFA-ACO applied to a network with 30 bus with a power demand 283.40 MW and the variable losses according to each method.

Tables 3 and 4 illustrate the results of the application of the methods ACO, FFA, PSO and FFA-ACO as well as the results of other researchers [1]-[2]-[3]-[4]-[5] with two cases. The first is a study with constant losses; the second case is a study with variable losses.

These results clearly show the effectiveness and performance of the FFA-ACO over other methods eitherin terms of function cost value or in terms of convergence time as shown in Figures 8,9 and 10.

Table 4. Comparison of different methods for IEEE 30 bus system (case study 2).

Bus	NLP [1]	TS [2]	DE-OPF [3]	EP [4]	IEP [5]	PSO	FFA-ACO
P_{G1}	176.26	176.04	176.00	173.848	176.23	186.045462	181.2728
P_{G2}	48.84	48.76	48.801	49.998	49.00	40.506530	50.1223
P_{G5}	21.51	21.56	21.334	21.386	21.50	19.989630	20.1240
P_{G8}	22.15	22.05	22.262	22.630	21.8115	10.912199	15.5418
P_{G11}	12.14	12.44	12.460	12.928	12.33	26.346145	10.0146
P_{G13}	12.00	12.00	12.000	12.000	12.01	12.809430	12.0000
P_L	9.48	/	9.466	/	/	5.8265	5.6754
Cost	802.40	802.29	802.394	802.62	802.46	802.262714	787.5593

[1]: Park .J.B ; [2]: Abido;[3]: Sayah et al;[4]: Yuan .X; [5]: Ongsakul .W

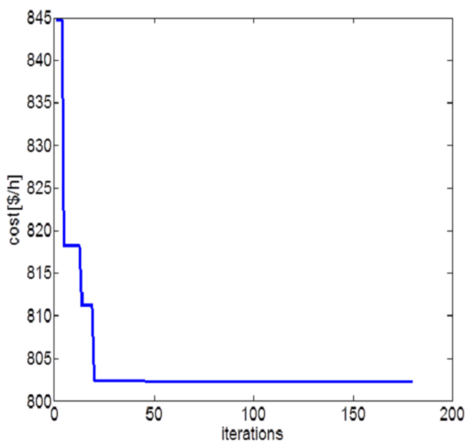

Fig. 8. The function cost values in different iterations for PSO method (case study 1)

For the ACO only, convergence is reached after 110 iterations and the best cost is equal to 801.7739 $/hr, and for the FFA the convergence is reached after 160 iterations and the best cost is equal to 801.0074 $/hr. Concerning the FFA-ACO hybrid technique the convergence is reached after 113 iterations and the cost reached is 787.5593 $/hr.

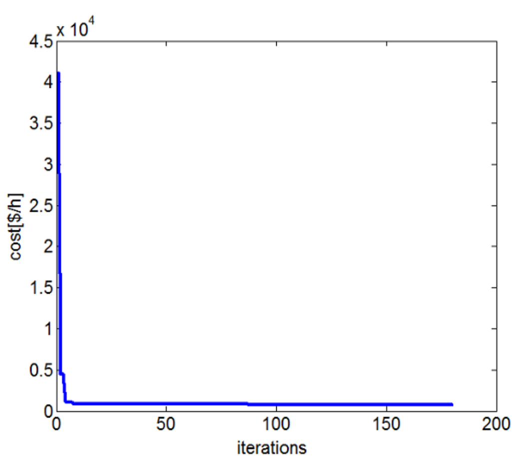

Fig. 9. The function cost values in different iterations for PSO method(case study 2)

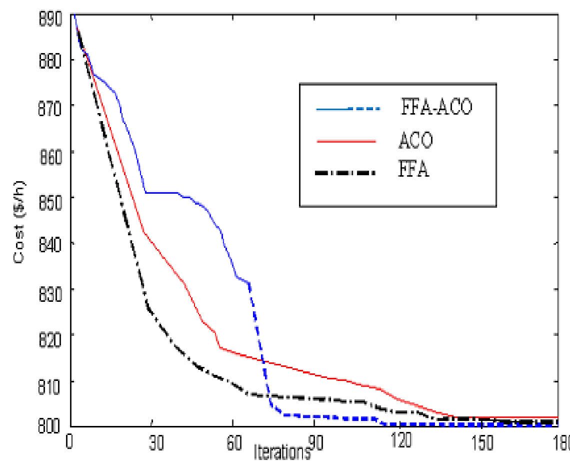

Fig. 10. The function cost values in different iterations for ACO, FFA methods and FFA-ACO approach

8. CONCLUSIONS

In this paper i have developed a hybrid method for solving EPD including active power dispatch using two Meta heuristic methods based on firefly and ant colony algorithms. The first considers the constant losses and the second studies variable losses. The method developed was tested on the IEEE 30 bus power system. The case studies have shown that this method is robust and can provide an optimal solution with fast computation time and a small number of iterations.
The method is very simple to apply in other optimization tasks. It needs to transform the treated problem to a mathematical model as an objective function with equalities and inequalities constraints.

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