Firefly Algorithm for Economic Power Dispatching With Pollutants Emission

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Bio-inspired algorithms become among the most powerful algorithms for optimization. In this paper, we intend to provide one of the recent bio-inspired metaheuristic which is the Firefly Algorithm (FF) to optimize power dispatching. For evaluation, we adapt the particle swarm optimization to the problem in the same way as the firefly algorithm. The application is done in an IEEE-14 and on two thermal plant networks. In one of the examples, we neglect power loss and pollutant emissions. The comparison with the particle swarm optimization (PSO), demonstrate the efficiency of firefly algorithm to reach the best cost in less than one second.
Keywords: *Firefly Algorithm, Economic Power Dispatching, Particle Swarm Optimization, Pollutant Emissions*

1 Introduction

Currently, a set of nature-inspired metaheuristics based on the natural behavior of birds, ants, swarms, and bees, have emerged as an alternative to rise above the difficulties presented by conventional methods in optimizations problems.
Economic power dispatching is one of the difficult optimization problems. Resolution by metaheuristics can avoid significant financial loss.
In this paper, we adapt the firefly algorithm to economic dispatching problem. For this, we describe in the second section the economic problem and its formulation. In the third section, we present the used metaheuristic, its origin and its parameters. In the fourth section, we describe our adaptation of the particle swarm optimization (PSO) and the Firefly algorithm (FF) to the problem. In the last section, we discuss the results of the metaheuristics on two networks. Finally, we give a conclusion.

2 Power Economic Dispatching

Description:
Economic dispatch problem has become a decisive task in the operation and planning of power system. The aim is to schedule the committed generating units output so as to meet the required load demand at minimum cost fulfilling all system operational constraints. Improvement can lead to significant cost saving (from 0, 03 $ to 0,20 $ per kWh) [4].
Methods in the literature:
Various conventional methods like nonlinear programming [32] [39], Bundle method [33], dynamic programming [45], mixed integer linear programming [6] [17] [18] [31] [39], quadratic programming [12], Lagrange relaxation method [12] [49], network flow method [14], direct search method [56] reported in the literature are used to resolve such problems.
Practically, economic dispatching problem is nonlinear, no convex with multiple local optimal points due to the inclusion of valve point loading effect, multiple fuel options with diverse equality and inequality constraints.
Conventional methods have failed to solve such problems as they are sensitive to initial estimates and converge into local optimal solution and computational complexity.
Heuristic optimization techniques based on artificial intelligence concepts operational research, such as Tabu search [29] [31], neural network [26] [28] [33] [36] [58],evolutionary, programming [36] [45]

[50] [64] and genetic algorithms [2] [7] [39] [51] [54] [57], simulated annealing [4] [54] [55],ant colony optimization [20] [47], particle swarm optimization [9] [10] [22] [23] [24] [25] [27] [39] [40] [41] [48] [50] [52] [53] [64] [65] provide the better solution. PSO has gained popularity as the best suitable solution algorithm for such problems.

Formulation :

Having a network with N generators nodes where:

p_{g_k} : Power of generator k.

p_L : Lost power.

p_D : Requested power.

Economic dispatch problem can be represented as a quadratic fuel cost objective function as described in (1).

$$f(p_g) = \sum_{k=1}^{n} f_k\,(p_{g_k}) \quad (1)$$

f : Total cost

f_k : Cost of node k

with considering equality constraint (2) to demand and inequality constraint (3).

$$\sum_{k=1}^{n} p_{g_k} - p_L = p_D \quad (2)$$

$$P_{g,\min} \leq p_{g_k} \leq P_{g,max} \quad (3)$$

A cost of a power generator p_{g_k} can be formulated by (4).

$$f_k\left(p_{g_k}\right) = c_k + b_k p_{g_k} + a_k p_{g_k}^2 + d_k \sin e_k (p_{g,min} - p_{gk}) \quad (4)$$

So that:

a_k , b_k , c_k :Power Cost coefficients

d_k , e_k : Thermal power Cost coefficients.

The 4th term is for thermal power but can be neglected.

Thermal Emission Constraint:

In the case of thermal power, the atmospheric pollutants such as sulphur oxides (SOx) and nitrogen oxides (NOx) caused by conventional thermal units can be modeled separately. However the total emission of these pollutants which is the sum of a quadratic and an exponential function can be expressed as (5) :

$$E\ (p) = \sum_{k=1}^{n} \alpha_k\, p_{gk}^2 + \beta_k\, p_{gk} + c_k + \eta_k e^{\delta_k p_{gk}} < ME \quad (5)$$

where: ME is the maximum allowable amount of pollutant during the dispatch period which is the EPA's hourly emission target [65] and $\alpha_k , \beta_k , c_k , \delta_k , \eta_k$ are emission coefficients.

3 Firefly Algorithm

Inspiration:

Fireflies, belong with family of Lampyridae, are small winged beetles capable of producing a cold light flashes in order to attract mates. They are believed to have a capacitor-like mechanism, that slowly charges until a certain threshold is reached, at which they release the energy in the form of light, after which the cycle repeats [11]

Firefly algorithm, developed by [60] is inspired by the light attenuation over the distance and fireflies' mutual attraction, rather than by the phenomenon of the fireflies' light flashing. Algorithm considers what each firefly observes at the point of its position, when trying to move to a greater light-source, than its own. Cold light is a light producing little or no heat.

Algorithm:

The Firefly Algorithm is one of the newest meta-heuristics developed by Yang [59] [60] [61] [62]. One can find few articles concerning the continuous firefly algorithm [1] [13] [15] [19] [30]. A validation of continuous firefly algorithm on stochastic functions is given in [59].

Sayadi et al. [42] proposed the first discrete version for permutation flow shop problem using a binary coding of solution and a probability formula for discretization. We can also find other discretization for economic problem such as [3][11][21].

Pseudo-code of the Firefly Algorithm (FF) may look as follows:

```
Procedure FF Metaheuristic (Nbr_gen: the
max. number of generations)
Begin
γ: the light absorption coefficient
Define the objective function of  f(x),
where x=(x1,........,xd) in domain d
Generate the initial population of fire-
flies or xi (i=1, 2 ,..., nb)
```

```
Determine the light intensity Ii at xi
via f(xi)
While (iter<Nbr_Gen)
For i = 1 to nb     //all nb fireflies
For j=1 to nb       //nb fireflies
if (Ij> Ii)
Attractiveness βi,j varies with distance
ri,j
move firefly i towards j with attrac-
tiveness βi,j
else
move firefly i randomly
end if
Evaluate new solutions
update light intensity Ii
End for j
End for i
Rank the fireflies and find the current
best
iter++  //iteration
End while
End procedure
```

Parameters:

In the firefly algorithm, there are five important issues:

- *Light Intensity*. In the simplest case for minimum optimization problems, the brightness I of a firefly at a particular location x can be chosen as: $I(x) \equiv 1/f(x)$
- *Attractiveness.* In the firefly algorithm, the main form of attractiveness function can be any monotonically decreasing functions such as the following generalized form:

$$\beta_{i,j} = \beta_0^* e^{-\gamma r_{i,j}} \quad (5)$$

Where $r_{i,j}$ is the distance between two fireflies i and j, β_0^* is the attractiveness where the distance is null and γ is a fixed light absorption coefficient.

- *Distance.* The distance between any two fireflies i and j at x_i and x_j can be the Cartesian distance as follows:

$$r_{i,j} = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \quad (6)$$

where $x_{i,k}$ is the k^{th} component of the i^{th} firefly.

- *Movement.* The movement of a firefly i attracted to another more attractive (brighter) firefly j, is determined by (7).

$$x_i = (1 - \beta_{i,j})x_i + \beta_{i,j}x_j + \alpha(rand - {}^1/_2) \quad (7)$$

where the first and second term is due to the attraction while the third term is randomization with α being the randomization parameter and "rand" is a generator of random numbers uniformly distributed in [0, 1].

4 Application to Power Economic Dispatching

Particles Swarm Optimization to economic dispatching:

The pseudo code of Particles swarm optimization seems to be as bellow:

```
Procedure PSO Meta-heuristic(Nbr_gen:
max number of generations)
Begin
φg, φp, ω: coefficients to be initialized
Define the objective function of f(x),
x=(x1...,xd) in domain d
Generate the initial population of par-
ticles pi (i=1,..., nb)
Determine the fitness fiti at pi via
f(pi)
Initialize the best fitness for each
particle fbesti=fiti and best positions
besti=pi
Determine the global best fitness
fgbest=min(fbesti) and its position gbest
While (iter<Nbr_Gen)
For i = 1 to nb           //all nb par-
ticle
      vi = ω vi +φp rand(besti-
xi)+φg rand(gbest-xi) //velocity
      Apply the velocity constriction in
d
      pi =pi+vi
      Apply the position constriction in
d
End for i
For i = 1 to nb           //all nb par-
ticle
     Calculate fiti
       if (fiti < fBesti)
              fBesti=fiti
              best=pi
       Endif
End for i
Determine the global best fitness
fgbest=min(fbesti) and its position gbest
iter++
End while
End procedure
```

where $Best_i$ is the best position of particle I with the fitness $fBest_i$ and gbest is the global best position of all particles with the fitness fgest.

In this study, we retain the principles below:

- *Fitness*. The fitness is simply the objective function

- *Position*. The new position is the calculate by the formula 8:

$$p_i = p_i + v_i \qquad (8)$$

where p_i is the current position of a particle i.

- *Velocity*. We keep the equation of velocity v_i of a solution i as shown in formula 9.

$$vi = \omega\ vi + \varphi p\ \mathrm{rand}(besti\text{-}xi) + \varphi g\ \mathrm{rand}(gbest\text{-}xi) \qquad (9)$$

where φ_g, φ_p, are coefficients initialized depending to sample .

The ω parameter decrease following the formula (10)[43]:

$$\omega = \omega_{\max} - \frac{(\omega_{\max} - \omega_{\min}) \times iter}{max\_gen} \qquad (10)$$

We initialize $\omega_{\max}, \omega_{\min}$ depending to the sample in the section V.

Firefly algorithm to economic dispatching:
To accelerate the FF algorithm, we suggest that alpha parameter increase following the formula (11):

$$\alpha = \frac{(\alpha_{\max} - \alpha_{\min}) \times iter}{max\_gen} - \alpha_{\max} \qquad (11)$$

Correction and Constriction:
Fireflies' attractiveness, randomly movements and Particle shifting provide float variables which sometimes do not respect constraints. We add before the intensity or the fitness update two functions. The first corrects position so that it stays in the domain $[p_{min}, p_{max}]$. The second corrects it so that the total power will be equal to request power. In the particle swarm optimization, the constriction of velocity is based on the same principle of the first corrector.
In the two algorithms we don't admit any violation of loss and demand constraint (formula (3)).

5 Computational Results

Data:
The implementation is done in C++ builder 32 bits in a personal computer with a Intel CPU of 22.67 Ghz and a RAM of 3,12 GO.
In a first example, we consider a IEEE network of 14 nodes [38] with two generators G_1 and G_2.There costs are:

$$f_1(P_{g1}) = 0.006\ Pg_1^2 + 1.5\ P_{g1} + 100$$
$$f_2(P_{g2}) = 0.009\ P_{g2}^2 + 2.1\ P_{g2} + 130$$

under equality constraint:

$$P_{g1} + P_{g2} - P_D - P_L = 0$$

And inequality constraint :

$$135 \le P_{g1} \le 195\ (MW)$$
$$70 \le P_{g2} \le 145\ (MW)$$

Requested Power is fixed to:
P_D=259 (MW)
Lost power is constant and equal to:
P_L=16.2 (MW)

In a second example, we consider a four unit thermal plant system (CS4)[43]. It has 4 generators where the total power losses PL are considered 0. The data for the 4 generators (cost coefficients and limits of generated powers) are presented in Table 1. The total power demanded in the system is PD=520 MW.

Table 1. Data of a CS4 thermal plant power System (2nd example)

Generator	a($/MW²)	b($/MW)	c($)	p_{min} (MW)	p_{max} (MW)
1	0.00875	18.24	750	30	120
2	0.00754	18.87	680	50	160
3	0.0031	19.05	650	50	200
4	0.00423	17.9	900	100	300

In the third example, we consider a network inspired from [34] with 5 generators. The emission is considered and it should be up to ME where ME=1700.
Requested Power is fixed to: PD=518(MW)
We consider a constant Loss power of PL=7.34 (MW)
under equality constraint: Pg – PD– PL = 0.

The data for the generators (cost coefficients and limits of generated powers) are presented in Table 2.

Table 2. Data of a 5 generators wind power System (3rd example)

Gene-rator	c($)	b($/MW)	a($/$MW^2$)	e($/$MW^2$)	d($/$MW^2$)	α	β	γ	η	δ	p_{min} (MW)	p_{max} (MW)
1	786.79	38.53	0.152	0.041	450	103.39	-2.444	0.031	0.503	0.0207	470	135
2	451.32	46.16	0.105	0.036	600	103.39	-2.444	0.031	0.503	0.0207	470	150
3	1049.99	40.39	0.028	0.028	320	300.39	-4.069	0.051	0.496	0.0202	340	73
4	1243.53	38.30	0.035	0.052	260	300.39	-4.069	0.051	0.496	0.0202	300	60
5	1658.57	36.30	0.021	0.063	280	320	-3.813	0.034	0.497	0.0200	243	73

In the three examples, PSO parameters are $\varphi_{g,}$=1.75, φ_p=2.75, $\omega_{\max} = 1$, $\omega_{\min} = 0.4$ while FF parameters are $\alpha_{\max} = 10, \alpha_{\min} = 0.02$, $\beta_0^* = 0.5$, $\gamma = 0.1$.
Results:

We optimize the first system with 10 fireflies in 50 iterations. We Remarque as shown in Figure 1 that the firefly algorithm reach a good cost of 790,48 $/h since the 16th itera-tion and its reach an optimum 781,95 $/h at the 21th iteration .

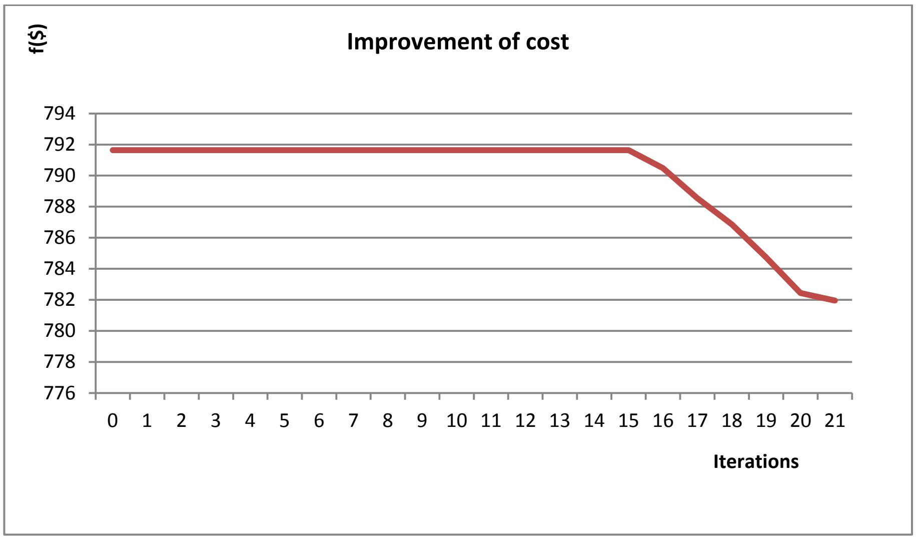

Fig. 1. Improvement of total cost with 10 fireflies in 50 iteration. 1st Exemple

The Table 3 shows the average CPU time, average total cost and minimum cost found in a simulation of 20 replications.

Table 3. The average and minimum output in 20 trials with the best generators powers. 1st Example

Trials Nb.	**avg. Cost**	**CPU time (hs.)**	**Min Cost**	**Pg1**	**Pg2**
10	783,26	0	781,958	195	80,2

In another simulation, we optimize IEEE-14 dispatching using 20 fireflies. We can ob-serve from Figure 2 that since initial solution of the first population at iteration 0 has the cost of 784,1 $/h. At the 3rd iteration the op-timizer can reach the optimum of 781,95 $/h.

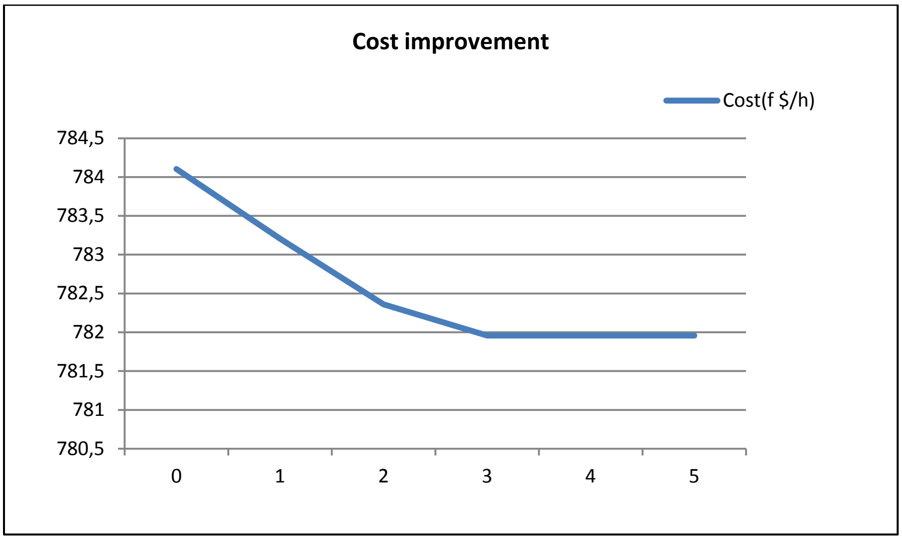

Fig. 2. Improvement of total cost with 20 fireflies in 50 iteration.1st example.

The firefly algorithm can find a cost function equal to 781,958 $/h at 20th iteration environ with only 10 fireflies and in a CPU time below 1 hundredth second.
An example of an optimization of the CS4 system with the same initial population is given in Figure 3.We clearly observe that the firefly algorithm is better than PSO one for this example.

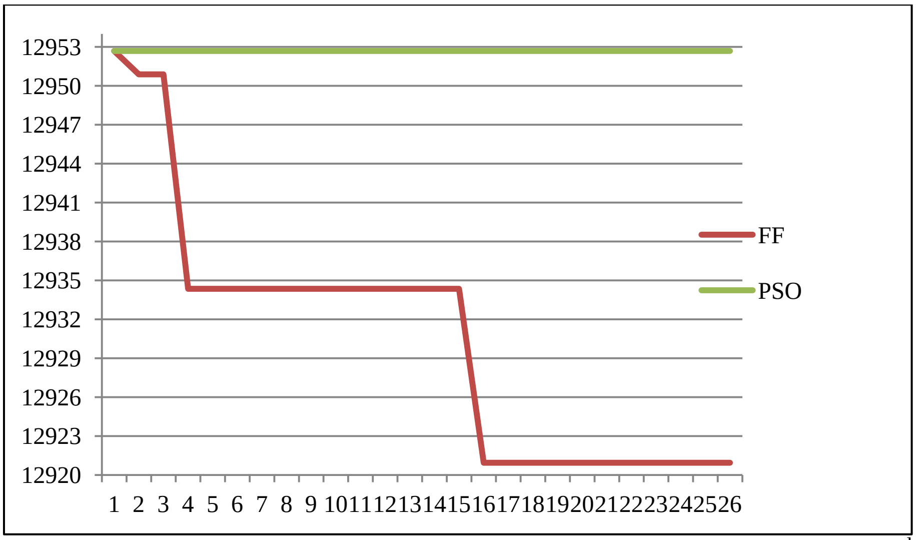

Fig. 3. Improvement of cost with 15 fireflies and 15 particles in 50 iterations, 2nd example.

The average , best and worst Costs as the average of CPU times in 100 trials are given in Figure 4.They can confirm that firefly algorithm get the best cost of 12919.78711 $ where the best cost found by PSO is 12920.01172 $. Firefly algorithm average and worst costs are also better than particle swarm optimization costs.

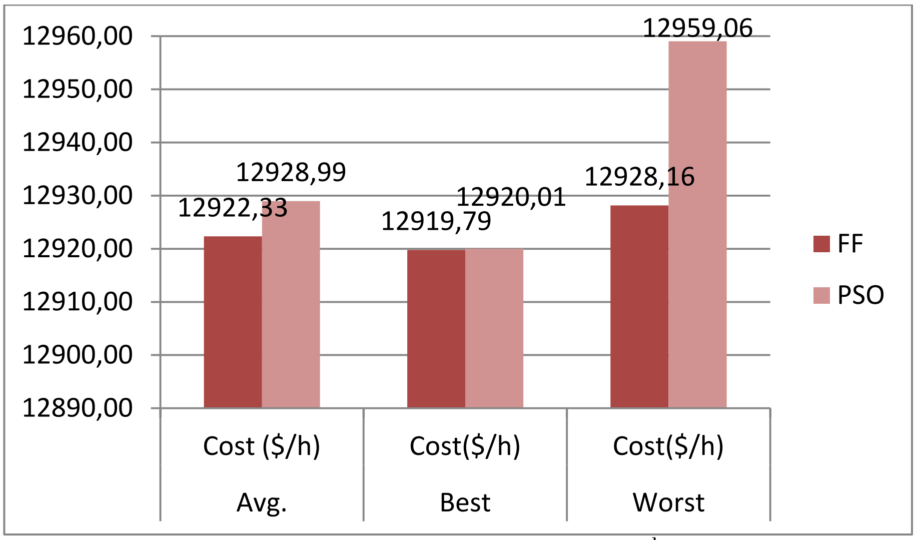

Fig. 4. Comparison of average, worst and best cost, 2^{nd} example, number of trials=100,number of iteration=50, number of particles=15.

The CPU time of PSO which is equal to 0.2619 hundredth seconds (Figure 5) seems to be less than FF time (0.8339 hundredth seconds). This is due that the firefly algorithm is based on the comparison of fireflies together so it has a complexity of O(N2) while the PSO algorithm is based only on the comparison of each particle with its best position in history so it has a complexity of O(N).

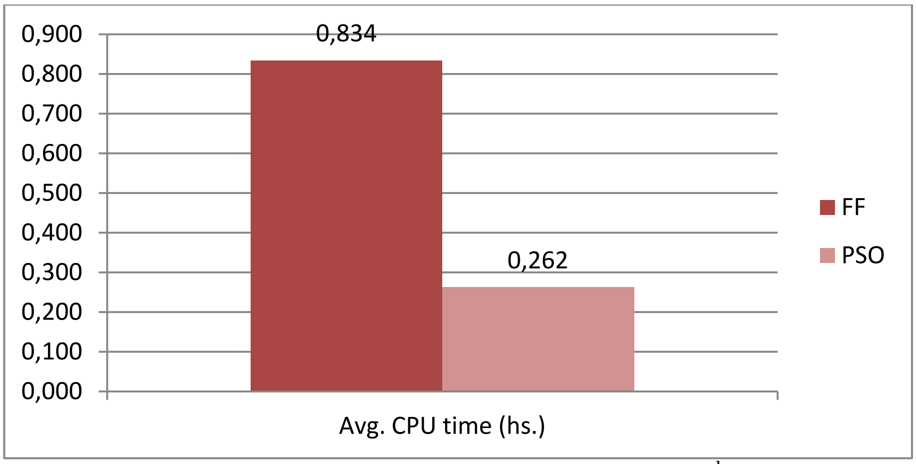

Fig. 5. Comparison of average CPU time(hundredth seconds), 2^{nd} example, number of trials=100,number of iteration=50, number of particles=15.

The rounded best powers are 91.3108 and 64.8567 MW

We optimize the second system with 6 fireflies in 50 iterations. We detect as shown in Figure 6 that the firefly algorithm reach a best cost of at the 6th iteration so it is undoubtedly faster than PSO algorithm in term of iterations.

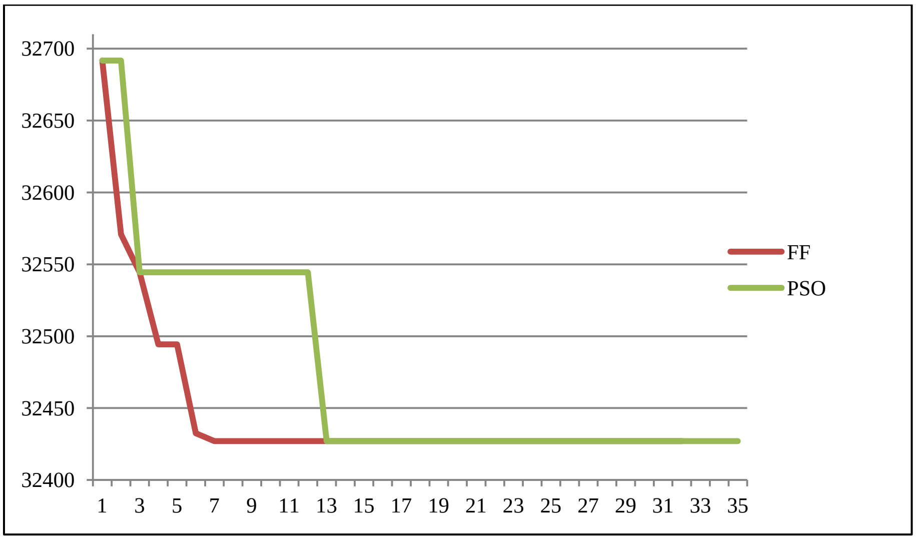

Fig. 6. Improvement of total cost with 15 fireflies or 15 particles in 50 iterations, 3rd example

One hundredth trials with 50 iterations give the results in Figure 7. We view that the firefly algorithm gives an optimum slightly litter than the PSO one.

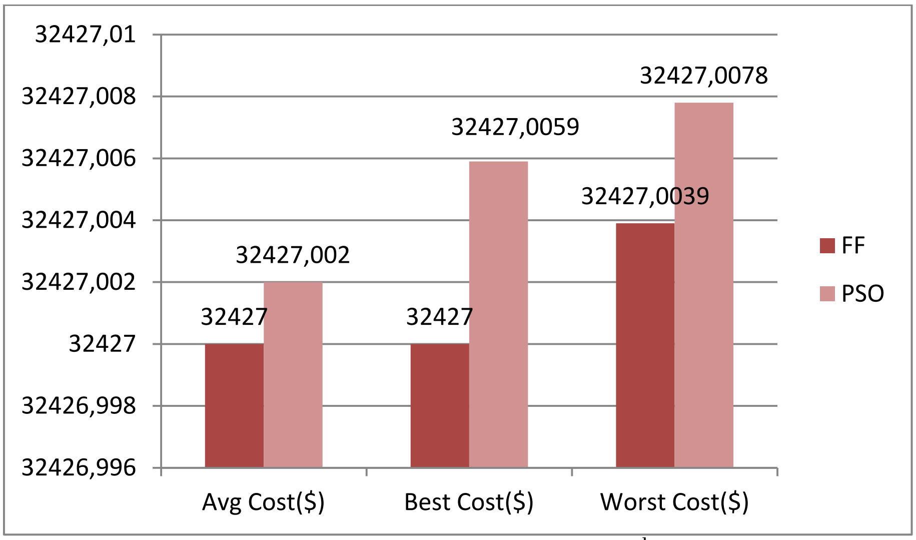

Fig. 7. Comparison of average, worst and best cost, 3rd example, number of trials=100,number of iteration=50, number of particles=15.

The average CPU time and the best emission found are given in Table 4.

Table 4. Comparison of average CPU time and best emission, 3rd example, number of trials=100,number of iteration=50, number of particles=15.

Algorithm	Avg. CPU time(hs.)	Best Emission
FF	36,44201	1617.878
PSO	0,519999	1617.873

We decrease the number of iterations to 20 and of particles and fireflies to 6 and we detect the same results with a CPU time of 10 hundredth seconds of FF and 0.1 hundredth second of PSO. We conclude that due to the emission constraint no improvement could be possible beyond the values found.

The best powers of the 5 generators are 150, 135, 73 ,60 and 107.33995056 MW.

6 Conclusion

In this paper we showed the efficiency and the feasibility of the recent algorithm which is the firefly metaheuristic to resolve economic power dispatching problem. This problem with nonlinear function has also the particularity to have hard constraints. So we avoid using any subjective penalty parameter to guarantee that it will be the constraints fulfilling. However, the firefly algorithm based on a comparison of fireflies together and the movements of them even if they are good, increase the chance to find the optimum. That is why the algorithm allows us to find easily a best cost on ieee-14 and on two thermal plant network dispatching with and without pollutant emission. Our Future works will focus in the comparison of this algorithm to economic dispatch test systems and other dynamic version with renewable power.

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