A hybrid FFA-MPSO algorithm for solving economic power dispatch problem with valve-point effect

N.Kherfane M.Younes R.L.Kherfane F.Khodja

Faculty of Technology Djillali Liabes University Sidi Bel Abbes, Alegria;

kherfanen@yahoo.fr

Abstract: *This paper developed a new method to solve the economic power problems (EPD) considering the valve-point effects in power systems. The method is based on a hybrid algorithm composed of FFA algorithm and micro Particle Swarm Optimization (MPSO) .The searching process starts with the FFA by initializing a group of random fireflies, then the search is pursued by the MPSO, then the best results (better than FFA) found from MPSO are also communicated to the FFA as an initial space search.*

The method suggested was applied to three cases different of power systems. The cost the property of convergence and the effectiveness of calculation of the method suggested were explored by the comparison with the recent existing techniques for problems of EPD to consider the valve-point effects.

Keywords: *Economic dispatch, Firefly Algorithm (FFA), micro Particle Swarm Optimization (MPSO), Power system, valve-point effects*

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) [3,4], quadratic programming (QP) [5], linear programming (LP) [6], and Interior Point Methods [7], Newton-based Method [8], Mixed Integer Programming [9], Dynamic Programming [10], Branch and Bound [11] 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-convexity. Applications of conventional optimization techniques such as the Gradient-based Algorithms are not adequate to solve this problem, because they 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.

Examples of these attempt include Tabu Search (TS) [12], Simulated Annealing (SA) [13], Genetic Algorithms [14], Evolutionary Programming (EP) [15], Artificial Neural Networks [16], Particle Swarm [17,18], Ant Colony Optimization (ACO) [19], Harmony Search Algorithm [20] . 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. For minimization/maximization problems the metaheuristic methods allow to find solutions closer to the optimum but with high cost in time.

To solve this problem, we have combined two meta-heuristic methods, the FFA and the MPSO. The searching process starts with the FFA by initializing a group of random fireflies, then the search is pursued by the MPSO, then the best results (better than FFA) found from MPSO are also communicated to the FFA as an initial space search. The process is repeated than until the final solution is reached.

The robustness of the proposed approach is tested and validated on the three cases different of power. The obtained results are compared with those in literature. The rest of this paper is organized as follows: Section 2 considers the Problem Formulation and the optimization under equality and inequality constraints. Section 3 discusses an explanation of the firefly algorithm (FFA).Section 4 discusses Particle Swarm Optimization (PSO). The approach (FFA-MPSO) is presented in section 5.Section 6 presents simulation results and discussion on solution quality. Conclusions are summarized in

Section7.

2. Problem Formulation

2.1. Conventional EPD problems

The goal of conventional EPD problem is to solve an optimal allocation of generating energy in a power system. The power balance constraint and the generating power constraints for all units should be satisfied. While satisfying the power balance equality constraint and several inequality constraints on the system... The EPD problem is generally formulated as follows:

$$f(x,u) \quad (1)$$

Subject to

$$g(x,u) = 0 \quad (2)$$

$$h(x,u) \le 0 \quad (3)$$

Where *g(x, u)* is the typical equality constraint, *h(x, u)* is inequality constraints. x is the vector of state variables consisting of slack bus power P_{G1}, load bus voltages V_{L1} , reactive power generator outputs Q_{G1} and transmission line loading S_{L1}. Hence x can be expressed as:

$$x^T = [P_{G1}, V_{L1}, ..., V_{LN_{PQ}}, Q_{G1}, ..., Q_{GN_G}, S_{L1}, ..., S_{LNL}] \quad (4)$$

Where N_{PQ}, Ng and NL are: the number of load buses, the number of generators and the number of transmission lines, respectively.

u is the vector of control variables consisting of generator real power outputs except at the slack bus P_G , generator voltages V_G , transformer tap settings T and reactive power injections Q_C . Hence, u can be expressed as

$$u^T = [P_{G2}, ..., P_{GNg} V_{G1}, ..., V_{GNg}, T_1, ..., T_{nt}, Q_{C1}, ..., Q_{Cnc}] \quad (5)$$

Where nt is the number of regulating transformers and nc is the number of VAR compensator.

2.2. Objective Functions

2.2.1. Minimization of Fuel cost

The goal of conventional EPD problem is to find an optimal allocation of generating powers in a power system. The power balance constraint and the generating power constraints for all units should be satisfied. In other words, the EPD problem (see fig. 2) 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 [21]. The total fuel cost function is formulated as follows:

$$f(P_G) = \sum_{i=1}^{Ng} f_i(P_{Gi}) \quad (6)$$

$$f_i(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i \quad (7)$$

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 and c_i are the fuel cost coefficients of unit i;

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

2.2.2. Non-smooth power economic dispatch

The fuel function is roughly expressed like quadratic function for each unit of generation in convex economic problems. This case involves bringing closer calculation and the results in a solution erroneous, consequently. So of various types of physical and operational constraints are added in the problem for the correction of the optimal solution, the problem transforms itself into problem of forced optimization nonlinear. Economic dispatch problem with the effect of point of valve is one of these problems, which is classified like non-convex problem and it is very difficult to find an optimal solution to him.

The inclusion of the effect of point of valve in the cost of fuel of the unit of generation provides a more suitable representation compared to the cost of fuel. While the point of valve is finalized with rises, the performance of fuel function includes a higher nonlinear series. For this reason, as for the study aimed at considering the effects of point of valve, a non-convex function is used.

In reality, the objective function has non differentiable points according to valve point loading effects. Therefore, the objective function should be composed of a set of non-smooth cost functions [22].

Multi-valve steam turbines based generating units are characterized by complex non-linear fuel cost function. The dotted line in the figure.1 is the variation of the performance cost function taking into accounts the valve effects [23]. To take account for the valve-point effects, sinusoidal terms are added to the quadratic cost functions as follows:

$$f(P_G) = \sum_{i=1}^{Ng} \left(a_i P_{Gi}^2 + b_i P_{Gi} + c_i + \left| d_i \times \sin\left\{ e_i \times \left(P_i^{\min} - P_i \right) \right\} \right| \right) \quad (8)$$

Where d_i, e_i are: the cost coefficients for i^{th} generator reflecting valve-point effects.

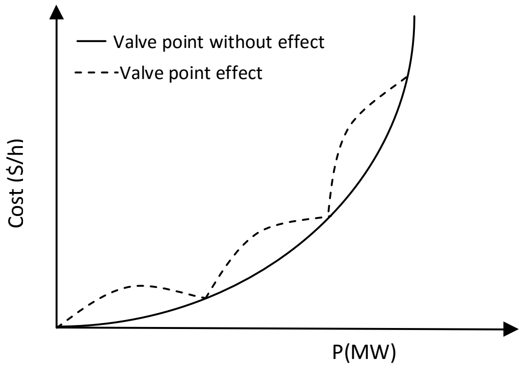

Fig. 1. Input–output characteristics of the generation units.

2.2.3. Minimization of real power loss

The main objective is to minimize the network active power loss while satisfying a number of operating constraints. The objective function may be expressed as:

$$P_L = \sum_{k=1}^{nl} g_k \left[V_i^2 + V_j^2 - 2V_iV_j \cos(\alpha_i - \alpha_j)\right] \qquad (9)$$

Where g_k is the conductance of a transmission line k connected between i^{th} and j^{th} bus, Vi, Vj, α_i, α_j are the voltage magnitudes and phase angles of i^{th} and j^{th} bus respectively, nl is the total number of transmission lines.

2.3. Problem constraints

2.3.1. 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:

$$\sum_{i=1}^{Ng} P_{Gi} = P_{load} + P_L \qquad (10)$$

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 equation (5), which represents the losses as a function of the output level of the system generators.

$$P_L = \sum_{i=1}^{N_G}\sum_{j=1}^{N_G} P_i B_{ij} P_j + \sum_{i=1}^{N_G} B_{0i} P_{Gi} + B_{00} \qquad (11)$$

Where B_{ij} is the transmission loss coefficient, P_i, P_J the power generation of i^{th} and j^{th} units.

B_{0i} is the i^{th} element of the loss coefficient vector

B_{00} is the constant loss coefficient.

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

P_{load} : is the total load demand.

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

N_G is the number of generator units in the system;

Equality constraints on real and reactive power at each bus are given by equations (14) and (15).

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{nb} V_j \left[G_{ij} \cos(\alpha_i - \alpha_j) - B_{ij} \sin(\alpha_i - \alpha_j)\right] = 0 \qquad (12)$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{nb} V_j \left[G_{ij} \sin(\alpha_i - \alpha_j) - B_{ij} \cos(\alpha_i - \alpha_j)\right] = 0 \qquad (13)$$

where $i = 1, 2, ..., nb$, nb is the number of buses; Q_{Gi} is the reactive power generated at the i^{th} bus; P_{Di} and Q_{Di} are the bus real and reactive load, respectively; G_{ij} and B_{ij} are the transfer conductance and susceptance between bus i and bus j, respectively; V_i and V_j are the voltage magnitudes at bus i and bus j, respectively; and α_i and α_j are the voltage angles of i and bus j, respectively.

2.3.2. Active power generation limits

Generation constraints: Generator voltages, real power outputs and reactive power outputs are restricted by their lower and upper bounds as follows:

$$V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max} \qquad (14)$$

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max} \qquad (15)$$

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max} \qquad (16)$$

Transformer constraints: Transformer tap settings are restricted by their minimum and maximum limits as follows:

$$T_i^{\min} \le T_i \le T_i^{\max} \qquad (17)$$

Shunt VAR constraints: Reactive power injections at buses are restricted by their minimum and maximum limits as:

$$Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max} \qquad (18)$$

Security constraints: These include the constraints of voltage magnitudes at load buses and transmission line loadings as follows:

$$V_{Li}^{\min} \le V_{Li} \le V_{Li}^{\max} \qquad (19)$$

$$S_{li} \le S_{li}^{\max} \qquad (20)$$

3. Firefly Algorithm (FFA)

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 Yang Xin-She at Cambridge University in 2008 [24]. It uses the following three idealized rules:
1) All fireflies are unisex so that a firefly will be attracted to other fireflies regardless of their sex [25].
2) Attractiveness is proportional to their brightness; thus for any two flashing fireflies the less bright will move towards the brighter one [26]. 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. On the first rule, each firefly attracts all the other fireflies with weaker flashes [27].
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

The light intensity I varied with distance r [28] is expressed by the following equation:

$$I(r) = I_0 e^{-\gamma r^2} \quad (21)$$

As a firefly's attractiveness is proportional to the light intensity [29] seen by adjacent fireflies, we can now define the attractiveness β of a firefly by:

$$\beta(r) = \beta_0 e^{-\gamma r^2} \quad (22)$$

Where I is the light intensity, I_0 is the original light intensity, γ is the light absorption coefficient, β_0 is the attractiveness [30].

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 as follows:

$$r_{ij} = \left| x_i - x_j \right| = \sqrt{\sum_k^d (x_{i,k} - x_{j,k})^2} \quad (23)$$

Where x_{ik} is the k^{th} component of the spatial coordinate x_i of i^{th} firefly the movement of a firefly i is attracted to another more attractive firefly j is determined by

$$x_{i+1} = x_i + \beta_0 e^{-\gamma r_{ij}^2}\left(x_j - x_i\right) + \alpha\left(rand - \frac{1}{2}\right) \quad (24)$$

Where the first term is the current position of a firefly [31], 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)* [32]. As we will see in this implementation of the algorithm, we will use $\beta_0 = 0.1$, $\alpha \in (0,1)$ and the attractiveness or absorption coefficient $\gamma = 1.0$ which guarantees a quick convergence of the algorithm to the optimal solution [33].

4. Particle Swarm Optimization Method

PSO is a promising evolutionary technique which has some advantages over other similar optimization techniques, PSO is easier to implement and there are fewer parameters to adjust, and its algorithm requires less computation time and less memory. In addition, PSO is flexible and thus, can easily be handled with objective functions. But PSO has also some defects, such as premature convergence. To overcome this problem, PSO is associated [34] with another algorithm that is close, namely the Genetic algorithm [35]. The PSO was originally developed by Eberhart and Kennedy in 1995 [36, 37] using a population-based stochastic algorithm. Similarly to genetic algorithms [38], and evolutionary algorithm approach, the PSO is an evolutionary optimization tool of swarm intelligence field based on a swarm (population), where each member is seen as a particle, and each particle is a potential solution to the problem under analysis. Each particle in PSO has a randomized velocity associated to it, which moves through the space of the problem. However, unlike genetic algorithms, PSO does not have operators, such as crossover and mutation. PSO does not implement the survival of the fittest individuals; rather, it implements the simulation of social behavior [39]. PSO, however, allows each particle to maintain a memory of the best solution that it has found. The mathematical model for PSO is as follows.

$$V_i^{t+1} = w \times V_i^t + c_1 \times rand_1 \times \left(Pbest_i - X_i^t\right) + c_2 \times rand_2 \times \left(gbest_i - X_i^t\right) \quad (25)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (26)$$

Where
V_i^t: Velocity at iteration t the i^{th} particle in the swarm
X_i^t: Position at iteration t the i^{th} particle in the swarm

Pbest$_i$: called the local leader or the personal best position, represents the best position found by the i^{th} particle itself so far;
gbest: called the global leader or the global best position, represents the global best position found by neighbors of this particle so far;
i: number of particles
w : inetia weight factor
c_1 , c_2: acceleration constant
$rand_1$, $rand_2$: uniform random value in the range [0.1]
The use of linearly decreasing inertia weight factor *w* has provided improved performance in all the applications. Its value is decreased linearly from about 0.9 to 0.4 during a run. Suitable selection of the inertia weight provides a balance between global and local exploration and exploitation, and results in less iteration on average to find a sufficiently optimal solution. Its value is set according to the following equation:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \qquad (27)$$

Where w_{max}, w_{min}: are both random numbers called initial weight and final weight respectively
$iter_{max}$: The maximum iteration number
iter : The current iteration number

The procedure of particle swarm optimization technique can be summarized in the Figure 2.

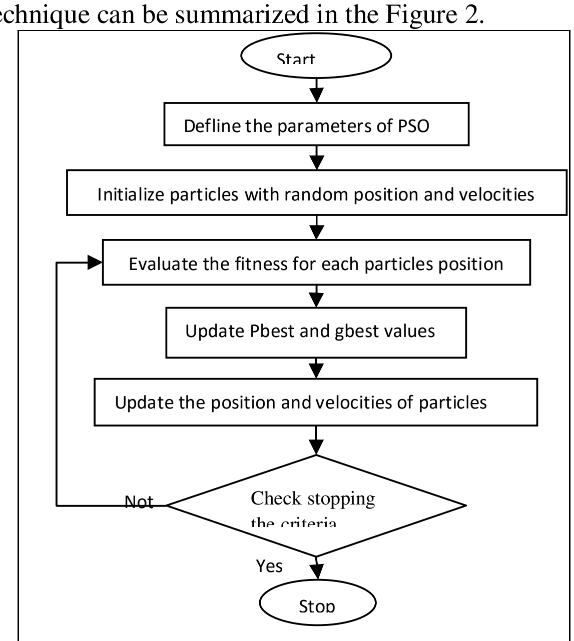

Fig. 2 Flow chart of PSO

Micro–Particle Swarm Optimization (MPSO) is a PSO with the size, which is considered to be rather small. Typically, the population evolves and converges (locally) in a few iterations (about 4–5) because of the small population size.

5. Firefly Algorithm-micro Particle Swarm Optimization (FFA-MPSO)

The balance between exploration and exploitation is achieved with approach FFA-MPSO. The searching process starts with the FFA by initializing a group of random fireflies, then the search is pursued by the MPSO, the results found by the FFA are used as starting points for MPSO.
As we saw in the previous section, the Micro-Particle Swarm Optimization (MPSO) works with a small number of populations is designed to best exploit the search space with low time of convergence.
Then, the best results (better than FFA) found from MPSO are also communicated to the FFA as an initial space search. The process is repeated than until the final solution is reached. Fig 2, 3 and 4 shows the mechanism search of the combined global–local search without communication and considering communication. The following steps summarize description of the proposed algorithm:
Step 1. Run FFA (with the max to iterations)
Step 2. The best control variables optimized based FFA are communicated to MPSO and considered as the initial research space (with the max to iterations).
Step 3. Communicate the best solution found from MPSO to FFA and considered as the initial research space.
Step 4. The process is repeated than until the final solution is reached (the solution is repeated).
This approach can quickly and accurately find an optimum solution.

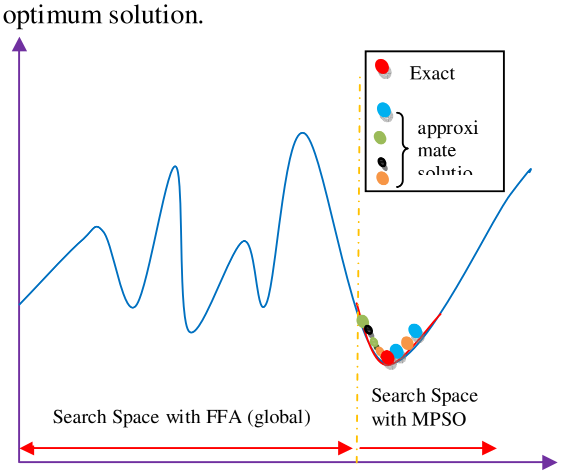

Fig.3. Search space with FFA-MPSO

6. Simulation results

The proposed FFA-MPSO approach based on global and local search is developed in the Matlab programming language using 7.04 version. In order to validate the robustness of the proposed method, three networks were been considered, the first one 6-bus with 3 generators for a load demand of 210 MW, the second one with IEEE 14 buses and 5 generators for a load demand of 259 MW, the third one with IEEE 30 buses and 6 generators for a load demand of 283.4 MW and with two cases, with valve point effect and without valve point effect. The generators data and B-coefficients are shown respectively in Tables 1, 4, 7 [40, 41].

6.1. 6 bus 3 generators system

Table.1 Cost coefficients, active power generation limits of the generation units and transmission loss coefficients

	a_i	b_i	c_i	d_i	e_i	P_{Gi}^{min}	P_{Gi}^{max}
PG1	0.00533	11.669	213.1	130	0.0635	50	200
PG2	0.00889	10.333	200	90	0.0598	37.5	150
PG3	0.00741	10.833	240	100	0.0685	45	180

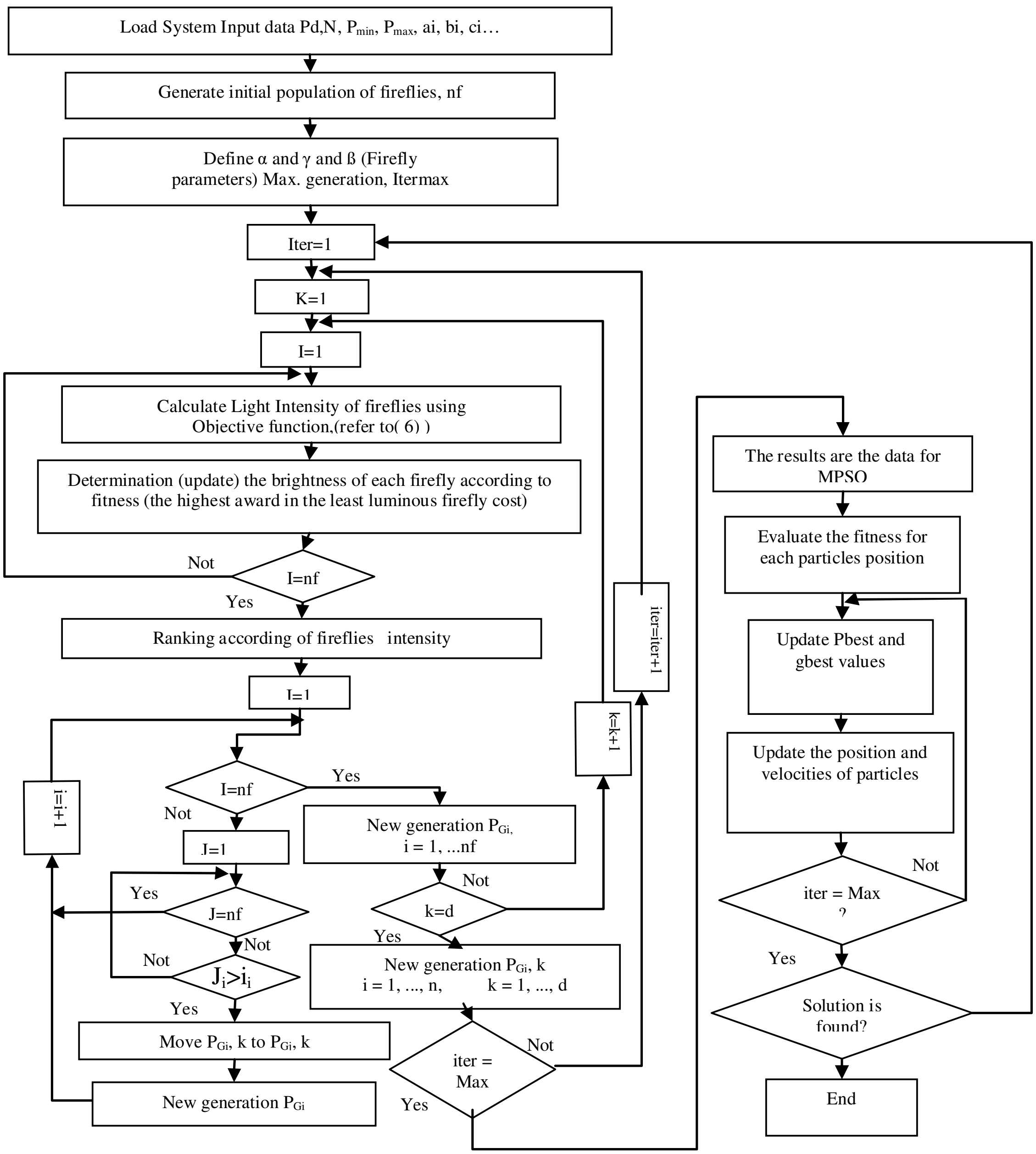

Fig.4. Flow chart for EPD using FFA-MPSO

$$[B] = \begin{bmatrix} 0.0552 & 0.0062 & -0.0046 \\ 0.0062 & 0.0253 & 0.0064 \\ -0.0046 & 0.0064 & 0.0286 \end{bmatrix}$$

$$[B_0] = [0.0046 \quad 0.0035 \quad 0.0019]$$

$$[B_{00}] = [0.00055711]$$

6.1.1. Case 1: quadratic fuel cost minimization

As seen in Table 2, since the Three-Unit system only has 3 units, it is very simple; all the evolutionary methods get the same solution. From the Table, we can see that for the Three-Unit system, the proposed FFA-MPSO method can get the best solution among the FFA and MPSO in the literatures. The total generation cost from the FFA-MPSO method is reduced at a value of 3110.661462 comparing to the FFA method, and it is also reduced comparing to the MPSO method.

Table 2
Optimization results of FFA-MPSO approach for 6 bus 3 generator system

	Best (cost) MPSO	Best (cost) FFA	Best (cost) FFA-MPSO
PG1(MW)	53.759002	51.416361	50.073271
PG2(MW)	69.969447	72.448310	73.878281
PG3(MW)	90.967464	90.921083	90.878914
Fuel cost($/h)	3113.887331	3111.787641	3110.661462
Real loss (MW)	4.6959	4.7858	4.8305
T(S)	0.1258	0.2025	0.01014

By exploiting the figure5, we can see that convergence is reached after 80 iterations and the best cost is equal to 3110.661462 $/h, As seen in Table 2, in the Three-Unit system, the CPU times of the FFA-MPSO method is a little less than the FFA method and MPSO, it is worth 0.01014 S .The FFA-MPSO method can get a better computation.

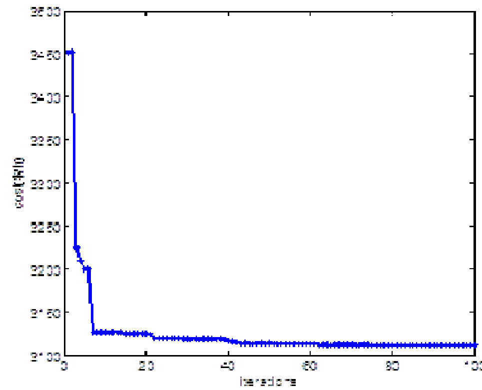

Fig.5. The function cost values in different iterations for FFA-MPSO method (IEEE-6 BUS)

6.1.2. Case 2: quadratic fuel cost Curve with Sine Components

in this case, only the cost curves of the generators are replaced by valve point loading effects .The objective function is to be expressed with the model to Eq(8).

The best results of the proposed approach compared with other methods are illustrated in Table 3 which shows clearly the superiority of the proposed approach.

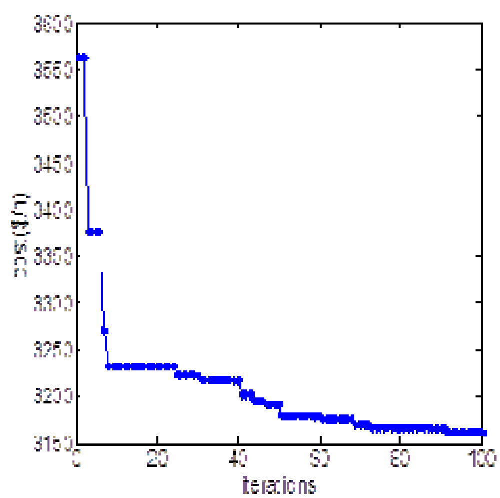

Fig.6. The function cost values (with valve point effect) in different iterations for FFA-MPSO method (IEEE-6 BUS)

Table.3 Optimization results of FFA-MPSO approach with valve point effect for 6-bus.

Methods	P_{G1} (MW)	P_{G2} (MW)	P_{G3} (MW)	Loss (MW)	Cost ($/h)	T (S)
GA [42]	53.2604	88.9645	74.7693	6.9939	3252.46	1.0310
GA-APO [42]	61.6467	95.1632	60.5402	7.3460	3341.77	0.812
NSOA [42]	50.0000	86.0678	79.7119	5.779	3205.99	0.0140
PSO[43]	50.4739	74.1958	90.8627	5.5324	3189.82	0.3117
MSG-HP [43]	50.000	74.7428	90.7680	5.5117	3188.146	0.2469
IABC-LS[44]	50	74.3459	90.8604	5.2063	3185.2942	0.008
IABC[44]	50.0028	74.5208	90.6764	5.2001	3185.8511	0.007
NHM [45]	50	90	75.87	5.87	3202.25	0.013
GA [45]	53.26	88.96	74.76	6.99	3252.45	1.031
HGA[45]	54.45	115.68	47.58	7.71	3294.80	0.812
FFA	99.4739	37.50000	78.8057	5.7796	3166.312609	0.258
FFA-MPSO	50.0000	37.50000	128.2797	5.7797	3161.4546	0.01125

Not heuristic method (NHM)

We saw the utility to draw the attention to the two last lines of table 3, it is very clear that this hybridization FFA-MPSO with valve point effect for 6-bus exceeds the other method exposed in the same table, the cost in this case is very reduced while arriving at a value of 3161.4546 ($/h) much better than the others.

CPU times of the FFA-MPSO method is a little less than the FFA method, it is about 0.01125 S and convergence is reached after 100 iterations.

Table.4 Cost coefficients, active power generation limits of the generation units and transmission loss coefficients.

	a_i	b_i	c_i	d_i	e_i	P_{Gi}^{min}	P_{Gi}^{max}
PG1	0.0016	2	150	50	0.0630	50	200
PG2	0.01	2.5	25	40	0.0980	20	80
PG3	0.025	1	0	0	0	15	50
PG6	0.00834	3.25	0	0	0	10	35
PG8	0.025	3	0	0	0	10	30
B-Coef							

$$[B]=\begin{bmatrix} 0.0212 & 0.0085 & -0.0009 & 0.0021 & 0.0007 \\ 0.0085 & 0.0206 & -0.0041 & 0.0037 & 0.0001 \\ -0.0009 & -0.0041 & 0.0395 & -0.0207 & -0.0251 \\ 0.0021 & 0.0037 & -0.0207 & 0.0613 & -0.0071 \\ 0.0007 & 0.0001 & -0.0251 & -0.0071 & 0.0406 \end{bmatrix}$$

$$[B_0]=[-0.0002 \quad 0.003 \quad -0.0017 \quad 0.0101 \quad -0.0038]$$

$$[B_{00}]=[0.00085357]$$

Let us return now to a system with IEEE 14 buses and 5 generators for a load demand of 259 MW, let us consider two cases (with valve point effect /and without valve point effect):

6.2.1. Case 1: quadratic fuel cost minimization (without valve point effect):

in table 5, we notice that the two methods MPSO and FFA are very robust, the best cost reaches a value of 829.597328 **$/h** with the first method, and a lower value of 827.286908 **$/h** with the second method while arriving at a value much better of 826.975457 **$/h** with the hybridization of the two methods.

CPU times of the FFA-MPSO method is a little less than the FFA method and MPSO, it is worth 0.008569 S. The FFA-MPSO method can get better computation efficiency.

Table 5

Optimization results of FFA-MPSO approach for IEEE-14 bus.

	Best (Cost) MPSO	Best (cost) FFA	Best (cost) FFA-MPSO
PG1 (MW)	196.952247	199.812783	199.987575
PG2 (MW)	29.370439	31.132178	30.724979
PG3 (MW)	19.732174	16.115501	16.366466
PG8 (MW)	10.599661	10.427850	10.081301
PG11(MW)	10.389557	10.297221	10.225370
Fuel cost ($/h)	829.597328	827.286908	826.975457
real loss (MW)	8.0441	8.7855	8.3857
T(S)	0.1212	0.3256	0.008569

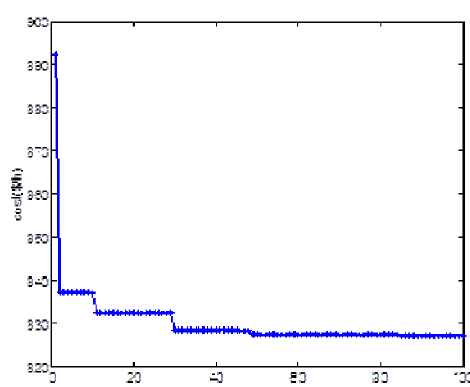

Fig.7. The function cost values in different iterations for FFA-MPSO method (IEEE 14 BUS)

From Fig. 7, we can get that, for all the systems, the ascend speeds at the beginning are high, the FFA-MPSO method can reach to the optimum solution quickly about 100 iterations. FFA-MPSO method is demonstrated to have a better convergence property.

6.2.2. Case 2: quadratic fuel cost Curve with Sine Components (with valve point effect):

Let examine the table 6 and let use the technique with valve point effect, it is very easy to judge that the FFA-Method is very effective compared to the other methods: NHM [58], MSG-HP[53],PSO[53];NSOA [54]GA [54],GA-APO [54]. For the method FFA-MPSO, the cost reached a splendid value of 834.0395 \$/h in a time of convergence of 0.00985 S, convergence keeps the same number of 100 iterations.

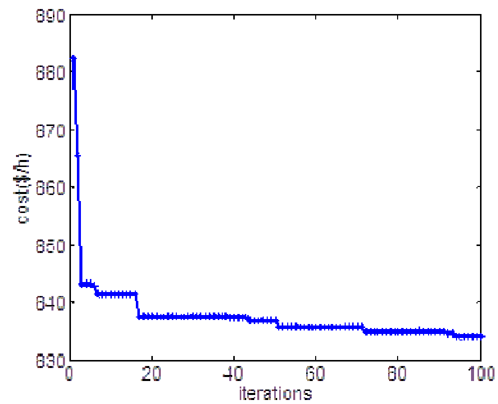

Fig.8. The function cost values (with valve point effect) in different iterations

Table 6. Comparison results of different methods for IEEE-5 machines 14-bus system for PD= 259 MW

Methods	P_{G1} (MW)	P_{G2} (MW)	P_{G3} (MW)	P_{G8} (MW)	P_{G11} (MW)	Loss (MW)	Cost (\$/h)	T(S)
NHM [45]	150	80	18.32	10	10	9.32	896.68	0.015
MSG-HP [43]	199.6923	20.0000	20.8157	15.5504	12.5069	9.5654	834.363	0.4617
PSO [43]	197.4696	20.0000	21.3421	11.6762	17.7744	9.2623	836.4568	0.3484
NSOA [42]	181.129	46.7567	19.1526	10.1879	10.7719	8.9977	905.5437	0.0150
GA [42]	172.765	26.6212	24.8322	23.4152	19.1885	7.8250	926.5530	0.3910
GA-APO [42]	172.765	26.6212	24.8322	23.4152	19.1885	7.8250	926.5530	0.3910
FFA	149.7331	52.0570	22.0184	29.7806	14.9760	9.5651	874.6183	0.398
FFA-MPSO	199.59965	20.0000	20.36441	17.692815	10.9084	9.5653	834.0395	0.00985

Not heuristic method (NHM)

We pass now to the application of this hybridization with the two cases on the system with IEEE 30 buses and 6 generators for a load demand of 283.4 MW

6.3. 30-bus 6 generators system

Table.7 Cost coefficients, active power generation limits of the generation units and transmission loss coefficients

	a_i	b_i	c_i	d_i	e_i	P_{Gi}^{min}	P_{Gi}^{max}
PG1	0.0016	2	150	50	0.0630	50	200
PG2	0.01	2.5	25	40	0.0980	20	80
PG3	0.025	1	0	0	0	15	50
PG6	0.00834	3.25	0	0	0	10	35
PG8	0.025	3	0	0	0	10	30
PG13	0.025	3	0	0	0	12	40
B-Coefficien							

$$[B]=\begin{bmatrix} 0.0224 & 0.0103 & 0.0016 & -0.0053 & 0.000 \\ 0.0103 & 0.0158 & 0.001 & -0.0074 & 0.000 \\ 0.0016 & 0.001 & 0.0474 & -0.0687 & -0.00 \\ -0.0053 & -0.0074 & -0.0687 & 0.3464 & 0.010 \\ 0.0009 & 0.0007 & -0.006 & 0.0105 & 0.011 \\ -0.0013 & 0.0024 & -0.035 & 0.0534 & 0.000 \end{bmatrix}$$

$$[B_0]=[-0.0005 \quad 0.0016 \quad -0.0029 \quad 0.006 \quad 0.001$$

$$[B_{00}]=[0.0011]$$

6.3.1. Case 1: quadratic fuel cost minimization (without valve point effect):

While referring in table 8, the best cost in the MPSO approach recorded a value of 918.620060 \$/h, the best cost in the FFA approach recorded a value of 917.730397 \$/h and finally the FFA-MPSO approach with its best value of 916.560132 \$/h always in a famous time of 0.00925 S.

Table 8
Optimization results of FFA-MPSO approach for IEEE 30 bus.

	Best (Cost) MPSO	Best (cost) FFA	Best (cost) FFA- MPSO
PG1 (MW)	198.295421	199.845008	199.698106
PG2 (MW)	41.390760	36.886954	41.489712
PG3 (MW)	16.111724	16.916511	19.156173
PG8 (MW)	13.008410	13.746261	10.013532
PG11(MW)	10.074959	13.382660	10.286364
PG13(MW)	15.869036	13.890634	14.382727
Fuel cost ($/h)	918.620060	917.730397	916.560132
real loss (MW)	11.3503	11.2680	11.6266
T(S)	0.025	0.0324	0.00925

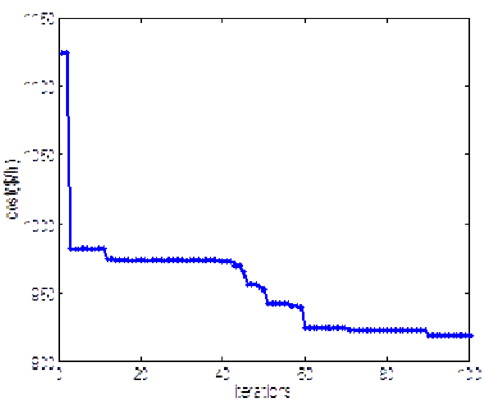

Fig .9. The function cost values in different iterations for FFA-MPSO method (IEEE 30 BUS)

From Fig. 9 in this case, we can get that, for all the systems, the ascend speeds at the beginning are high, the FFA-MPSO method can reach to the optimum solution about 60 iterations.

6.3.2. Case 2: quadratic fuel cost Curve with Sine Components (with valve point effect):

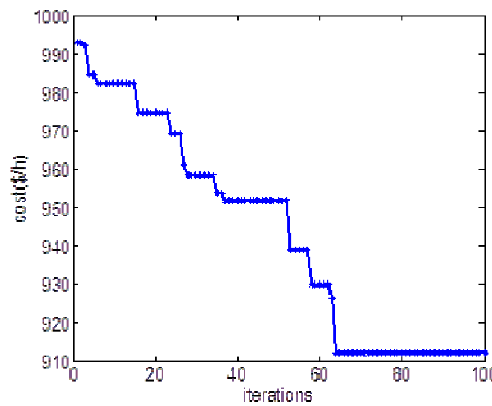

Fig.10. The function cost values (with valve point effect) in different iterations for FFA-MPSO method (IEEE 30 BUS)

The two last lines of the table 9 shows well that the approach FFA-MPSO keeps the first class compared to the other methods in the literature , the cost is of 911.4744 $/h , CPU times of the FFA-MPSO method is a little less than the FFA method and MPSO , it is worth 0.01 S in a very reduced number of iteration of 65.

Table.9 Comparison results of different methods for IEEE-30 bus system for PD= 283.4 MW.

Methods	P_{G1} (MW)	P_{G2} (MW)	P_{G3} (MW)	P_{G8} (MW)	P_{G11} (MW)	P_{G13} (MW)	Loss (MW)	Cost ($/h)	T (S)
GA [42]	150.724	60.8707	30.8965	14.2138	19.4888	15.9154	8.7060	996.0369	0.5780
GA-APO [42]	133.9816	37.2158	37.7677	28.3492	18.7929	38.0525	10.7563	1101.491	0.156
NSOA [42]	182.478	48.3525	19.8553	17.1370	13.6677	12.3487	10.4395	984.9365	0.0150
PSO [43]	197.8648	50.3374	15.0000	10.0000	10.0000	12.0000	11.8022	925.7581	0.3529
MSG-HP[43]	199.6331	20.0000	23.7624	18.3934	17.1018	15.6922	11.1830	925.6406	0.6215
NHM [45]	199.07	20	15	35	10	12	7.67	917.34	0.015
FFA	199.6525	20.0000	20.05800	18.0832	13.5375	21.2579	9.1891	**919.2158**	0.045
FFA-MPSO	199.5996	20.0000	21.2272	24.1004	13.0972	13.0454	7.6698	**911.4744**	0.010

Not heuristic method(NHM)

7. Conclusion

This paper has employed a hybrid method by mixing the FFA with the MPSO for solving the EPD EPD test cases considering the valve-point effects and a comparison with the results obtained using the problems with valve-point effects. The feasibility of the FFA-MPSO method was tested for three different FFA algorithm and the results reported in recent literatures was accomplished. The economic effect, convergence property and computation efficiency of the proposed method have been explored through the comparison with the recent techniques for the EPD problems considering the valve-point effects. The results show that the proposed hybrid FFA-MPSO method is very effective and it is very compatible for the EPD problem

References

[1].Carpentier, J. *Contribution a l'étude du dispatching économique*. Bulletin de la Société Française des Electriciens, (1962) vol. 3 pp. 431–447.

[2]. Vanderbei, J.R and Shanno,F.D. *An interior-point algorithm for nonconvex nonlinear programming*. Comput. Optim. Appl. (1999) vol. 13, pp. 231–252.

[3]. Bottero,M.H., Caliana,E.D.and A. R., Fahmideh Vojdani. *Economic dispatch using the reduced hessian*. IEEE Trans on Power Appra. Syst. (1982) vol. 101, pp. 3679-3688.

[4] Hock W, Schittkowski K, *A comparative performance evaluation of 27 nonlinear programming codes*. Computing by springer- verlag ; (1983) 30, 335–58.

[5] Reid, G. E., and Hasdorf, L. *Economic dispatch using quadratic programming*. IEEE Trans on Power Appara. Syst., (1973) vol. 92, pp. 2015-2023.

[6] Stott, B., and Hobson, E. *Power system security control calculation using linear programming*, IEEE Trans on Power Appara. Syst., (1978) vol. 97, pp. 1713-1731.

[7] Momoh, J. A., and Zhu, J. Z. *Improved interior point method for OPF problems*. IEEE Trans on Power System, (1999) vol. 14, pp.1114-1120.

[8] Sun, D.I., Ashley, B.,Brewer., Hughes, A.., and Tinney, W.F. *Optimal power flow by Newton approach*. IEEE Trans. On Power Systems, (1998) Vol.103, pp.2864-2880, 1984.

[9] Bahiense, L., Oliveira, G. C., Pereira, M., and Granville, S. *A mixed integer disjunctive model for transmission network expansion*. IEEE Trans. Power Syst., (2001) vol. 16, pp. 560–565.

[10] Dusonchet, Y. P. and El-Abiad, A. H.*Transmission planning using discrete dynamic optimization*. IEEE Trans. Power App. Syst., (1997) vol. PAS-92, pp. 1358–1371.

[11] Haffner, S., Monticelli, A. ; Garcia, A. , Mantovani J. and Romero, R. *Branch and bound algorithm for transmission system expansion planning using transportation model*. IEE Proc. Gener. Transm. Distrib., (2000) vol. 147, no.3, pp. 149-156.

[12] Glover, F. *Tabu search* - part i. ORSA Journal on Computing, (1986) 1(3), 190-206.

[13] Kirkpatrick, S., Gelatt, C. D., Vecchi, M. P. *Optimisation by simulated annealing*. Science, (1983) 220, 671-679.

[14] Lai, L. L,. Ma, J. T, Yokoyama, R., and Zhao, M. *Improved genetic algorithms for optimal power flow under both normal and contingent operation states*. Elec. Power Energy Syst. (1997) vol. 19, no. 5, pp. 287–292.

[15] Yuryevich .J., Wong.KP. *Evolutionary programming based optimal power flow Algorithm*. IEEE Trans Power Syst, (1999) vol. 14 n. 4, pp. 1245–1250.

[16] Maghrajabi, H., JARaface and Mohan Des. *Contingency Analysis of Bulk power system using Neural Network*. IEEE Trans on Power systems. (1998) pp1251-1254.

[17] Abido, M.A. *Optimal Power Flow Using Particle Swarm Optimization*. International Journal of Electrical Power and Energy Systems, (2002) Vol. 24, No. 7, pp. 563-571.

[18] Eberhart RC and Kennedy J. *A new optimizer using particle swarm theory, In Proceedings of 6th Internationl Symposium on Micro Machine and Human Science*, Nagoya,Japan, IEEE Service Center, Piscataway, NJ, (1995) pp. 39–43.

[19] Song,YH., Chou, CS, Stonham, TJ. *Combined heat and power dispatch by improved ant colony search algorithm*. Electr Power Syst Res; (1999) 52:115–21.

[20] Fesanghary M, Mahdavi M, Minary-Jolandan M, Alizadeh Y. *Hybridizing harmony search algorithm with sequential quadratic programming for engineering optimization problems*. Computer Methods in Applied Mechanics and Engineering Vol. 197, No. 33-40, 01.06.2008, p. 3080-3091.

[21] Alsac O, Stott B. *Optimal load flow with steady-state security*. IEEE Trans.Power Apparatus Syst; (1974) 93(3):745–51.

[22]Eric S. Fraga, Lingjian Yang, Lazaros G. Papageorgiou, *On the modelling of valve point loadings for power electricity dispatch*, Applied Energy (2012) 91 301–303

[23] Priyanka Roy, Pritam Roy, Abhijit Chakrabarti, *Modified shuffled frog leaping algorithm with genetic algorithm Crossover for solving economic load dispatch problem with valve-point effect*, Applied Soft Computing, (2013) 13, 4244–4252

[24] Yang X S. *Nature-Inspired Metaheuristic Algorithms*, Luniver Press. Bristol, 2008.

[25] Babak Amiri, Liaquat Hossain, John W Crawford, Rolf T Wigand. *Community Detection in Complex Networks: Multi–objective Enhanced Firefly Algorithm*. Knowledge-Based Systems, 2013, 46: 1–11.

[26] Gandomi A H, Yang X S, Talatahari S, Alavi A H. *Firefly algorithm with chaos. Communications in Nonlinear* Science and Numerical Simulation, (2013) 18(1): 89–98.

[27] Senapati M R, Dash P K. *Local linear wavelet neural network based breast tumor classification using firefly algorithm*, Neural Comput & Applic, (2013) 22:1591–1598

[28] Fister I, Yang X S, Brest J, Fister Jr I., *Modified firefly algorithm using quaternion representation*, Expert Systems with Applications, (2013) 40(8): 7220–7230.

[29] Ahmad Kazem, Ebrahim Sharifi, Farookh Khadeer Hussain, Morteza Saberi, Omar Khadeer Hussain. *Support*

vector regression with chaos-based firefly algorithm for stock market price forecasting. Applied Soft Computing, (2013) 13: 947–958.

[30] Yang X S. *Review of meta-heuristic and generalized evolutionary walk algorithm*. International Journal of Bio-Inspired Computation, 2011, 3(2): 77-84.

[31] Yang X S. *Firefly Algorithm. Engineering Optimization:An Introduction with Metaheuristic Applications*. Wiley, (2010), 221–230.

[32] Basu B, Mahanti G K. *Firefly and artificial bees colony algorithm for synthesis of scanned and broadside linear array antenna*. Progress in Electromagnetic Research B, (2011), 32: 169–190.

[33] Afshin Yazdani, Jayabarathi T, V. Ramesh V, Raghunathan T. Combined heat and power economic dispatch problem using firefly algorithm. Front. Energy, (2013), 7(2): 133–139.

[34] Yao F, Dong Z Y, Meng K, Xu Z, Ho-Ching Iu, Wong Kit Po *Quantum-inspired particle swarm optimization for power system operations considering wind power uncertainty and carbon tax in Australia 2012*. IEEE Transactions on Industrial Informatics (2012) 8:880–888.

[35] Younes M,Rahli M, Lahouari A K *Optimal Power Flow Based on Hybrid Genetic Algorithm*, Journal of Information Science and Engineering (2007) 23: 1801–1816

[36] Kennedy J, Eberhart R *Particle swarm optimization*. Proceedings of the IEEE international conference on neural networks, vol 4. IEEE Press, Piscataway, (1995) pp 1942–1948

[37] Eberhart RC, Kennedy J. *A new optimizer using particle swarm theory*. Proceedings of 6th International Symposium on Micro Machine and Human Science, IEEE Service Center, Piscataway, (1995) pp. 39–43, Nagoya, Japan

[38] Goldberg. D. E, *Genetic Algorithms in Search, Optimization and Machine Learning*, Addison Wesley Publishing Company. (1989)

[39] Coelho Leandro dos Santos, Viviana Cocco Mariani. *A novel chaotic particle swarm optimization approach using He non map and implicit filtering local search for economic load dispatch*. Chaos, Solitons and Fractals (2009) 39: 510–518

[40] Sayyid Mohssen Sajjadi, Ahmad Sadeghi Yazdankhah, Farzad Ferdowsi, *A new gumption approach for economic dispatch problem with losses effect Based on valve-point active power*, Electric Power Systems Research (2012) 92 81– 86

[41] Slimani L, Bouktir T *Optimal power flow solution of the algerian electrical network using differential evolution algorithm*. TELKOMNIKA, Indones J Electr Eng (2012) 10, 199–210

[42] Tahir Nadeem Malik, Azzam ul Asar, Mudasser F. Wyne, Shakil Akhtar, *A new hybrid approach for the solution of non convex economic dispatch problem with valve-point effects*, Electric Power Systems Research (2010) 80 (9) 1128–1136.

[43] C. Yasar, S. Özyön, *A new hybrid approach for non convex economic dispatch problem with valve-point effect*, Energy (2011) 36 (10) 5838–5845.

[44] Dogan Aydin, Serdar Özyön, *Solution to non-convex economic dispatch problem with valve by incremental artificial bee colony with local search point effects*, Applied Soft Computing (2013) 13, 2456–2466

[45] Sayyid Mohssen Sajjadi, Ahmad Sadeghi Yazdankhah, Farzad Ferdowsi, *A new gumption approach for economic dispatch problem with losses effect Based n valve-point active power*, Electric Power Systems Research (2012) 92 81–86

[46] Belkacem Mahdad, Kamel Srairi, *Solving practical economic dispatch using hybrid GA–DE–PS method*, Int J Syst Assur Eng Manag (2013).