

HYBRID FA AND GA FOR GENERATION ALLOCATION PROBLEM OPTIMIZATION

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Abstract: The paper presents a method for Economic Load Dispatch (ELD). Economic dispatch problem is basically an optimization problem where objective function may be highly non linear, non-convex, and no differentiable and may have multiple local minima. Therefore classical optimization methods may be trapped to any local minima and may not be able to reach the global minima. The solution to this problem was presented by the application of heuristics methods such as genetic algorithms unfortunately the long execution time and non-guaranteed in convergence to the global optimal solution contribute the main disadvantages of GAs. In this paper provides a solution to this problem through a hybrid method firefly algorithm-Particle Swarm Optimization.

Key words: Economic Load Dispatch (ELD), optimization, firefly algorithm, genetic algorithm.

1. Introduction

Economic Load Dispatch (ELD) are designed and operated to meet the continuous variation of power demand. The power demand is shared among the generating units and economic of operation is the main consideration in assigning the power to be generated by each generating units. Therefore, Economic load Dispatch (ELD) [1], is implemented in order to ensure for economic operation of a power system. Economic Dispatch problem is an optimization problem that determines the optimal output of online generating units so as to meet the load demand with an objective to minimize the total generation cost

Various mathematical methods and optimization techniques have been employed to solve for ELD problems. Among the methods that were previously employed include genetic algorithms (GAs), and evolutionary algorithm (EA) have been increasingly used to solve for power system optimization problems [2].

Since its introduction in late 1980's, GAs has been used to solve many power system optimization problems. It has been successfully employed to solve for economic load dispatch problem due its ability to model any kind of constraints using various chromosome-coding schemes according to specific problem. On the other hand, long execution time and non-guaranteed in convergence to the global optimal solution contribute the main disadvantages

of GAs. However, its long execution time posed its main disadvantage [3].

In this paper, a new method for solving ELD problem based on the hybrid genetic algorithm– firefly method.

The hybrid approach executes the two systems simultaneously and selects P individuals from each system for exchanging after the designated N iterations. The individual with larger fitness has more opportunities of being selected.

The feasibility study of the proposed technique was conducted on a practical system having 5 generating units. Several loading scenarios with a number of equality and in equality constraints were tested in order to demonstrate the effectiveness of the proposed technique. The results obtained from the proposed technique were also compared with those obtained from the GA optimization methods in order to assess the solution quality and computational efficiency.

2. Economic Load Dispatch formulation

Consider an Economic Load Dispatch (ELD) with i generators [4].

The ELD problem is to find the optimal combination of power generation that minimizes the total cost while satisfying the total demand. The cost function of ELD problem is defined as follows [5]:

$$\text{Min} \left\{ f(P_G) = \sum_{i=1}^{NG} f_i(P_{Gi}) \right\} \quad (1)$$

In (1), the generation cost function $f_i(P_{Gi})$ in US\$/h is usually expressed as a quadratic polynomial [6].

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

Where

$f(P_G)$: Total production cost (\$/h).

$f_i(P_{Gi})$ Is the cost of the ith generator in \$/h;

P_{Gi} The power output of generator i in MW;

a_i, b_i, c_i The cost coefficients of the i th generator.

In minimizing the cost, the equality constraint (power balance) and inequality constraint (power limits) should be satisfied.

- **Equality constraint**

$$\sum_{i=1}^{NG} P_{Gi} - \sum_{j=1}^{ND} P_{Dj} - P_L = 0 \quad (3)$$

Where

P_{Dj} : Active power load at bus j

P_{Gi} : Active power generation at bus i

P_L : Real losses

The transmission loss can be represented by the B-coefficient method as

$$P_L = \sum_i \sum_j P_{Gi} B_{ij} P_{Gj} \quad (4)$$

Where B_{ij} is the transmission loss coefficient, P_i, P_j the power generation of ith and jth units. The B-coefficients are found through the Z-bus calculation technique.

- **Inequality constraint**

The generation capacity of each generator has some limits and it can be expressed as

$$P_{Gi}^{\min} \leq P_{Gi} \leq P_{Gi}^{\max} \quad (5)$$

Where

$P_{Gi}^{\min}, P_{Gi}^{\max}$: Lower and upper limit of active power generation at bus i

N: Number of bus

ND: Number of load buses

NG: Number of generator

3. Description of Firefly Algorithm

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

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

1) All fireflies are unisex so that a firefly will be attracted to other fireflies regardless of their sex.

2) Attractiveness is proportional to their brightness; thus for any two flashing fireflies the less brighter will move towards the brighter one. The attractiveness is proportional to the brightness and they both decrease as their distance increases. If there is no brighter firefly than a particular one it will move randomly [7].

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 [8]. All fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex.

Secondly, attractiveness is proportional to their brightness which is reversely proportional to their distances.

For any two flashing fireflies, the less bright one will move towards the brighter one. The attractiveness is proportional to the brightness and they both decrease as their distance increases. If there is no brighter one than a particular firefly, it will move randomly. Finally, no firefly can attract the brightest firefly and it moves randomly.

The brightness of a firefly is affected or determined by the landscape of the objective function. For a maximization problem the brightness can simply be proportional to the value of the objective function. Other forms of brightness can be defined in a similar way to the fitness function in genetic algorithms based on these three rules.

3.1 Attractiveness

In the firefly algorithm there are two important issues: the variation of light intensity and the formulation of the attractiveness. For simplicity, we can always assume that the attractiveness of a firefly is determined by its brightness which in turn is associated with the encoded objective function [9].

In the simplest case for maximum optimization problems, the brightness I of a firefly at a particular location x can be chosen as $I(x)$ corresponding to $f(x)$. However, the attractiveness β is relative; it should be seen in the eyes of the beholder or judged by the other fireflies. 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 .

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:

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

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

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

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

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:

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

where β_0 is the attractiveness at $r = 0$. As it is often faster to calculate $1/(1 + r^2)$ than an exponential function, the above expression, if necessary, can conveniently be

replaced by $\beta = \frac{\beta_0}{1 + e r^2}$. 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

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

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 as follows:

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

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

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

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 $\beta_0 = 0.1$, $\alpha \in [0, 1]$ and the attractiveness or absorption coefficient $\gamma = 1.0$ which guarantees a quick convergence of the algorithm to the optimal solution.

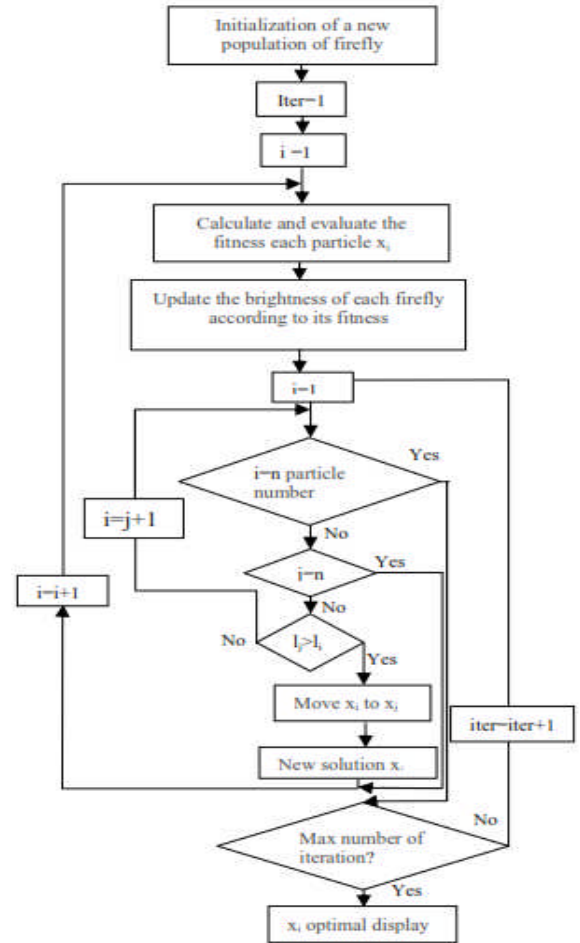


Fig. 1. Flow chart of firefly algorithm.

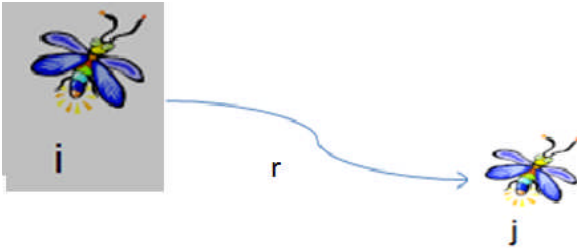


Fig. 2. Movement of fireflies.

4. Genetic Algorithm

The genetic algorithm is a search algorithm based on the mechanics of natural selection and natural genetics [10]. As summarized by Tomassini [11], the main idea is that in order for a population of individuals to adapt to some environment, it should behave like a natural system. This means that survival and reproduction of an individual is promoted by the elimination of useless or harmful traits and by rewarding useful behavior. The genetic algorithm belongs to the family of evolutionary algorithms, along with genetic programming, evolution strategies, and evolutionary programming. Evolutionary algorithms can be considered as a broad class of stochastic optimization techniques. An evolutionary algorithm maintains a population of candidate solutions for the problem at hand. The population is then evolved by the iterative application of a set of stochastic operators. The set of operators usually consists of mutation, recombination, and selection or something very similar [12].

Globally satisfactory, if sub-optimal, solutions to the problem are found in much the same way as populations in nature adapt to their surrounding environment. Using Tomassini's terms, genetic algorithms (GAs) consider an optimization problem as the environment where feasible solutions are the individuals living in that environment.

The degree of adaptation of an individual to its environment is the counterpart of the fitness function evaluated on a solution. Similarly, a set of feasible solutions takes the place of a population of organisms.

An individual is a string of binary digits or some other set of symbols drawn from a finite set. Each encoded individual in the population may be viewed as a representation of a particular solution to a problem. In general, a genetic algorithm begins with a randomly generated set of individuals. Once the initial population has been created, the genetic algorithm enters a loop [13]. At the end of each iteration, a new population has been produced by applying a certain number of stochastic operators to the previous population. Each such iteration is known as a generation [14].

The evolutionary cycle can be summarized as follows:

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Generation = 0
Seed population
While not (termination condition) do
Generation = generation + 1
Calculate fitness
Selection
Crossover
Mutation
end while

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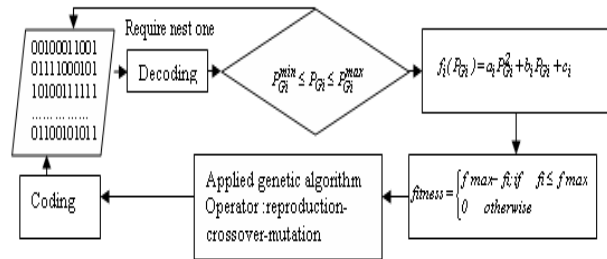


Fig.3. Simple flow chart of the GA

5. Genetic Algorithms Assisted by firefly algorithm

The hybrid approach executes the two systems simultaneously and selects P individuals from each system for exchanging after the designated N iterations. The individual with larger fitness has more opportunities of being selected. The main steps of the hybrid approach are depicted below:

1. Initialize GA and FA subsystems.
2. Execute GA and FA simultaneously.
3. Memorize the best solution as the final solution and stop if the best individual in one of the two subsystems satisfies the termination criterion.
4. Perform the hybrid process if generations could be divided exactly by the designated number of iterations N. Select P individuals from both sub-systems randomly according to their fitness and exchange. Go to step 3.

6. Simulation Results

The proposed method in this paper is been compared to the GA and the FA by applying to two tests systems (case 1 and case2).

Case 1

First, proposed algorithm is tested for the 6-generator system. This system has a single quadratic cost function for each generator. As a sample system, IEEE 30-bus system, which has 6-generator, is chosen. Total power demand D is set to 189.2 MW.

Case 2

Second, proposed algorithm is tested for the 7-generator, IEEE 57 bus system [15], which consists of 7 thermal generators.

The values of fuel cost coefficients are given in Table 1, Total load demand of the system is 1250.8 (MW), and 7 generators should satisfy this load demand economically. The results obtained from the proposed method are shown in Tables 4-5. This method has been tested 25 times.

Two test cases are considered, specifically, the first test case ignores the transmission losses. The second test case, the transmission line losses are calculated and maintained constant (PL = 19.06MW).

First Variant

The first test case ignores the transmission losses (PL = 0.00 MW), table 4, figure 4.

Second Variant

Transmission line losses are calculated and maintained constant (PL = 19.06MW), table 5, figure 5.

Table 1 Generators parameters of the IEEE 30 Bus

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

Table 2 Generators parameters of the IEEE 57 Bus

Bus	p_{Gi}^{\min} (MW)	p_{Gi}^{\max} (MW)	Cost coefficients		
			a_i	b_i	c_i
P_{G1}	0.0	575.88	0.01	0.30	0.20
P_{G2}	0.0	100.00	0.01	0.30	0.20
P_{G3}	0.0	140.00	0.01	0.30	0.20
P_{G6}	0.0	100.00	0.01	0.30	0.20
P_{G8}	0.0	550.00	0.01	0.30	0.20
P_{G9}	0.0	100.00	0.01	0.30	0.20
P_{G12}	0.0	410.00	0.01	0.30	0.20

Table 3. EPD results for load 189.2 (30 bus)

	FA	BGA	RGA	GA-FA
$P_{G1}(MW)$	65.010627	44.839351	50.0012	43.8139
$P_{G2}(MW)$	19.957552	70.894148	39.9898	57.1967
$P_{G3}(MW)$	23.444470	12.426175	25.0067	21.7218
$P_{G4}(MW)$	40.818984	21.038463	36.3094	29.8614
$P_{G5}(MW)$	11.124227	2.104106	17.5255	14.9448
$P_{G6}(MW)$	22.813034	30.062627	9.99999	15.5570
$P_D(MW)$	189.2	189.2	189.2	189.2
Cost (\$/h)	589.841591	574.154619	561.838	553.633

Table 4 Results of GA-FA compared with GAMatpower, GA and FA for the IEEE 57-bus system, (PL = 0.00 MW)

Variable	GAMatpower OPF[15]	GA	FA	GA-FA
$P1(MW)$	262.352	269.9591	305.12976	301.49463
$P2(MW)$	100.000	98.8967	99.078087	74.938124
$P3(MW)$	140.000	136.554	131.99147	117.55363
$P4(MW)$	100.000	91.9394	97.704647	99.231235
$P5(MW)$	275.537	245.5221	276.20137	295.46947
$P6(MW)$	99.9999	98.9920	93.520327	48.916911
$P7(MW)$	272.265	308.1162	246.76597	281.84984
Total fuel cost(\$/h)	3062.89	3044.442	3042.398	3016.627
PL(MW)	0.00	0.00	0.00	0.00

Table 5 Results of GA-PSO compared with GAMatpower, GA and FA for the IEEE 57-bus system. With the constant losses = 19.06

Variable	GAMatpower OPF[15]	GA	FA	GA-FA
$P1 (MW)$	277.149	289.04	343.399	262.296
$P2 (MW)$	100.000	96.851	99.349	96.4467
$P3 (MW)$	140.000	134.83	134.872	138.410
$P4 (MW)$	100.000	87.664	97.4055	99.0715
$P5 (MW)$	277.282	303.55	219.134	292.827
$P6 (MW)$	100.000	95.319	99.6873	87.8319
$P7 (MW)$	275.403	260.98	275.176	291.326
Total fuel cost (\$/h)	3173.982	3185.44	3171.99	3166.72
PL (MW)	19.06	19.06	19.06	19.06

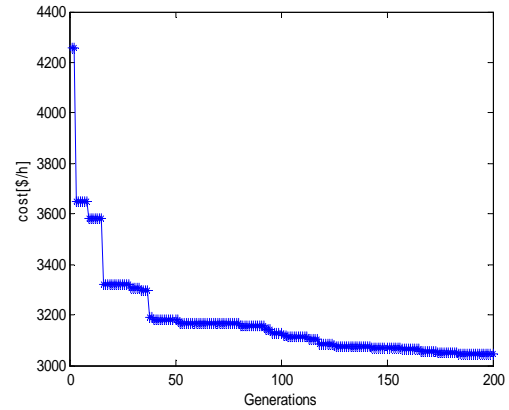


Fig. 4 The generation cost evolution during The iterative procedure with the losses=0

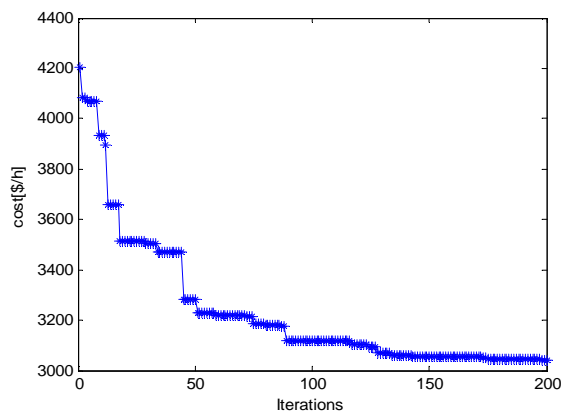


Fig. 5 The generation cost evolution during the iterative Procedure, with the constant losses= 19.06MW

7. Conclusion

Firefly (FA) is a relatively recent heuristic search method that is based on the idea of collaborative behaviour in biological populations. FA is similar to the Genetic Algorithm (GA) in the sense that they are both population-based search approaches and that they both depend on information sharing among their population members to enhance their search processes using probabilistic rules.

The objective of this research is the combination of these two methods to improve their effectiveness (solution quality),

The feasibility of the proposed algorithm is demonstrated on two systems IEEE 30 bus and IEEE 57-bus. The results show that the proposed algorithm is applicable and effective in the solution of ELD problems that consider nonlinear characteristics of power systems. GA-FA can generate an efficiently high quality solution and with more stable convergence,

The advantage of GA-FA over other method is modelling flexibility, sure and fast convergence.

References

1. Zimmerman, R.D.; Murillo-Sánchez, C.E.; Thomas, R.J.: *MATPOWER's Extensible Optimal Power Flow Architecture*, Power and Energy Society General Meeting, 2009 IEEE, pp. 1–7, July 26–30, 2009.
2. Rahimullah B.N.S., Ramlan E.I., Rahman T.K.A.: *Evolutionary Approach for Solving Economic Dispatch in Power System*. In Proceedings of the IEEE/PES National Power Engineering Conference, vol.1, pp. 32 – 36, Dec 2003.
3. Wong K.P. , Wong Y.W.:*Genetic and Genetic / Simulated-Annealing Approaches to Economic Dispatch*, Proc. IEE Gen. Trans.Dist., vol.141, no. 5, pp. 507 – 513, Sept 1994.
4. Younes M., Rahli M., Koridak H.: *Economic power dispatch using evolutionary algorithm*, Journal of Electrical engineering, Vol. 57, No. 4, , 211–217,2006.
5. Gaing Z. L.: *Constrained dynamic economic dispatch solution using particle swarm optimization*, in Proc. IEEE Power Engineering Society General Meeting, pp. 153-158, 2004.
6. Chakrabarti R., Chattopadhyay P. K., Basu M., Panigrahi C. K.: *Particle swarm optimization technique for dynamic economic dispatch*, IE(I) Journal-EL, vol. 87, pp. 48-54, 2006.
7. Sayadi .M. K. , Ramezani R., Ghaffari-Nasab N.: *A discrete firefly meta-heuristic with local search for makespan minimization in permutation flow shop scheduling problems*, International Journal of Industrial Engineering Computations, pp. 1 –10, 2010.
8. Yang .X.S.: *Firefly algorithms for multimodal optimization*, Stochastic Algorithms: Foundations and Applications Lecture Notes in Computer Sciences, vol. 5792, pp. 169–178, 2009.
9. Yang .X. S.: *Firefly algorithm, stochastic test functions and design optimisation*, International Journal of BioInspired Computation, vol. 2 n. 2, pp. 78 –84, 2010.
10. Goldberg, D. E.: *Genetic Algorithms in Search, Optimization, and Machine Learning*. Boston: Addison-Wesley; 1989.
11. Tomassini M.: *Parallel and distributed evolutionary algorithms: A review*. In K. Miettinen et al., editor, Evolutionary Algorithms in Engineering and Computer Science, pages 113–133. John Wiley and Sons, 1999
12. Ongsakul .W., Tantimaporn T.: *Optimal power flow by improved evolutionary Programming*, Electr Power Components Syst, vol. 34 n.1, pp. 79 –95; 2006.
13. Younes M., Rahli M.: *Dispatching Economique par l'intelligence Artificielle (Economic Dispatch by Artificial Intelligence)*. Proceeding ICEL'2005, Vol.02,pp.16-21,13-15 November 2005. U.S.T Oran, Algeria.
14. Younes M., Rahli M., Koridak H.:*Economic power dispatch using evolutionary algorithm*, Journal of Electrical engineering, Vol. 57, No. 4, , 211–217,2006.
15. Younes, M., Rahli, M., Koridak L.A.: *Optimal Power Flow Based on Hybrid Genetic Algorithm*, Journal of Information Science and Engineering, Vol. 23, pp. 1801-1816, 2007.