# Bakhta Naama, Kaouther Dahmani, Amel Abrouche and Hamid Bouzeboudja

Department of Electrical Engineering, Laboratory of sustainable development of electrical energy (LDDEE), University of Science and Technology, Mohamed Boudiaf (USTO-MB), Oran, Algeria

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# Solving the economic dispatch by new hybrid algorithm

Abstract. The problem of economic dispatch is the minimization of the total cost of production by satisfying the demand of the load. The resolution of this problem is a way of managing an electricity production system taking into account the constraints of equalities and inequalities, in other words it is to find the optimal production for a given combination of units in operation. The appearance of meta-heuristic methods which are part of artificial intelligence, has effectively contributed to solving this problem. Bee colony optimization is a very recent family of meta-heuristics. Its principle is based on the behavior of real bees in life. Bees have properties that are quite different from those of other insect species. They live in colonies, building their nests in tree trunks or other similar enclosed spaces. In this paper, we will apply the optimization by colony of bees in test systems of different sizes with the aim of minimizing the cost of production of electrical energy by taking into account the effect of the valve points of the power plants. In order to see the effectiveness of the proposed algorithm, it has been compared with other algorithms in the literature.

Streszczenie. Problem ekonomicznej wysyłki polega na minimalizacji całkowitego kosztu produkcji poprzez zaspokojenie zapotrzebowania na ładunek. Rozwiązanie tego problemu to sposób zarządzania systemem wytwarzania energii elektrycznej z uwzględnieniem ograniczeń równości i nierówności, czyli znalezienie optymalnej produkcji dla danej kombinacji pracujących jednostek. Pojawienie się metod metaheurystycznych wchodzących w skład sztucznej inteligencji skutecznie przyczyniło się do rozwiązania tego problemu. Optymalizacja kolonii pszczół to bardzo nowa rodzina metaheurystyk. Jego zasada opiera się na zachowaniu prawdziwych pszczół w życiu. Pszczoły mają właściwości zupełnie odmienne od właściwości innych gatunków owadów. Żyją w koloniach, budując gniazda w pniach drzew lub innych podobnych zamkniętych przestrzeniach. W tym artykule zastosujemy optymalizację przez rodzinę pszczół w układach testowych różnej wielkości w celu minimalizacji kosztów produkcji energii elektrycznej poprzez uwzględnienie wpływu punktów zaworowych elektrowni. Aby sprawdzić skuteczność zaproponowanego algorytmu, porównano go z innymi algorytmami dostępnymi w literaturze. (Rozwiązanie wysyłki ekonomicznej za pomocą nowego algorytmu hybrydowego)

Keywords: economic dispatch problem, genetic algorithm, bee colony algorithm, hybrid algorithm, valve-point effect. Słowa kluczowe: problem ekonomicznej wysyłki, algorytm genetyczny, algorytm kolonii pszczół, algorytm hybrydowy, efekt punktu zaworowego.

(3)

# Introduction

Optimal power distribution is therefore the basic computer tool allowing the network manager to determine the conditions for safe and economical operation of the electro-energy system. The Optimal Power Distribution procedure uses mathematical programming-based methods to determine the optimum setting of system control variables while satisfying a specified set of operational and safety requirements. The problem of economic dispatching (ED) or the distribution of the economic load is a particular case of the optimal distribution of powers.

Economic dispatching (ED) is a static optimization problem. The objective is to minimize generator fuel consumption and overall system operational cost by determining the optimum output of each generator under the system load constraint conditions within a number of system operational constraints. The fundamental problem of economic dispatching is related to the set of input and output characteristics of power plants.

Several classical optimization techniques such as gradient method, lambda iteration method, Newton's method, linear programming, interior point method and dynamic programming have been used to solve the economic power distribution problem.

New methods have been developed to solve the (ED) problem such as genetic algorithm (GA) [1-3], tabu search (TS) [4], simulated annealing (SA) [5,6], evolutionary programming (EP) [7,8], particle swarm optimization (PSO) [9,10] and differential evolution (DE) [11,12], cuckoo search algorithm (CSA) [13], the bat algorithm (BA) [14,15].

In this paper, a bee colony algorithm is proposed to obtain improved results in the ED problem, taking into account valve point effects.

# **Problem Formulation**

The objective of ED problem is to minimize the total cost of production while respecting the constraints of equality and inequality. The fuel cost curve for any unit is assumed to be approximated by segments of quadratic functions of the generator output active power.

# A. Economic Dispatch (ED) formulation

For a given power grid, the problem can be described as an optimization of the total fuel cost function as defined by equation (1) under a set of operating constraints.

 $F_{T} = \sum_{i=1}^{N} F_{i} (P_{i}) = \sum_{i=1}^{N} (a_{i}P_{i}^{2} + b_{i}P_{i} + c_{i})$ (1)Where:  $F_T$  is total fuel cost of generation in the system (\$/hr),  $a_i$ ,  $b_i$ , and  $c_i$  are the cost coefficient of the *i* th generator, P<sub>i</sub> is the power generated by the *i* th unit and N is the number of generators. The cost is minimized subjected to the following constraints:

Generation capacity constraint,

(2) 
$$P_i^{min} \le P_i \le P_i^{max}$$
;  $i = 1, 2, ... 3$   
Power balance constraint.

 $P_D = \sum_{i=1}^N P_{i-}P_L$ Where  $p_i^{min}$  and  $p_i^{max}$  are the minimum and maximum power output of the *i* th unit, respectively.  $P_D$  is the total load

demand and  $P_l$  is total transmission loss. The transmission loss  $P_L$  can be calculated by using *B* matrix technique and is defined by (4) as,

(4) 
$$P_L = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{0i} P_i + B_{00}$$

Where,  $B_{ij}$ ,  $B_{0i}$  and  $B_{00}$  are transmission loss coefficients.

# B. ED problem with valve point effect

Large thermal power plants have several steam inlet valves, which are used to control the power delivered by the unit. Every time you start to open an inlet valve, there is a sudden increase in losses. The valve point effect is considered to be a practical constraint to the operation of generators. The valve point effect brings a ripple in the heat rate function and makes the fuel cost function highly nonlinear, discontinuous and having multiple local optimal. A second-order quadratic cost function is added with the rectified sinusoidal equation for accurate modeling of the generator cost function taking into account valve point effect as follows:

(5) 
$$F_T = \sum_{i=1}^{N} (a_i P_i^2 + b_i P_i + c_i + |e_i \times \sin(f_i \times (P_i^{min} - P_i))|)$$

Where  $F_T$  is total fuel cost of generation in (\$/hr) including valve point loading,  $e_i$ ,  $f_i$  are fuel cost coefficients of the *i* th generating unit reflecting valve-point effects.

# Artificial Bee Colony Algorithm for Economic Dispatch Problem

The ABC (Artificial Bee Colony) algorithm is developed by Karaboga and Basturk in 2005, by inspecting the behaviors of real bees to find the source of food, which is called nectar, and share information of sources of food for other bees in the nest. In this algorithm, artificial bees are defined and classified into three groups: employing bees (bees that search for food), spectators (bees observation) and scouts (girl scouts) are in charge of finding new foods, (the new source nectar) [16]. For each food source, there is only an employing bee. That is to say, the number of employing bees is equal to the number of food sources [17]. If the employing bee of a site fails to find the food source, it must be necessarily become a scout to randomly search for new food sources. The worker bees share information with onlooker bees in a hive so that onlooker bees can choose a food source to explore.

The brief working principle of ABC as follows [18]:

# Step 1 Initialization

Determine the number of food source (SN)

Calculate vector of possible solution  $X_i=X_1$ ,  $X_2$ ...  $X_{SN}$ ;  $X_i$  is represent by the location of food source.

The fitness of each possible solution can be calculate using the following formula:

(6) 
$$Fitness_{i} = \begin{cases} \frac{1}{1+F_{i}}, & \text{if } F_{i} \ge 0\\ 1+abs(F_{i}), & \text{otherwise} \end{cases}$$

# Step 2 Employed Bees

Employed Bees find the new food source position  $V_{ii}$  using:

(7) 
$$V_{ij} = X_{ij} + \phi_{ij} * (X_{ij} - X_{kj})$$

Where  $\phi_{ij}$  is a random number between [-1, 1], and  $k \in \{1, 2, ..., NS\}$  and  $j \in \{1, 2, ..., D\}$  are index randomly chosen. *D* is number of problem variables.

If the new position is found better than the old position, a new position is memorized and otherwise it is removed. The greedy selection method is used to determine the best solution.

# Step 3 Onlooker Bees

In this phase, onlooker bees will search the best results according to the probability (*Pi*) as follows:

(8) 
$$P_i = \begin{cases} \frac{Fitness_i}{\sum_{j}^{NS} Fitness_j} \end{cases}$$

The solution with better fitness value has high probability of being selected by an onlooker bee in order to exploit the solution near to global optimal value.

# Step 4 Scout Bees

After several trials, unimproved food location (solution) will explore other possible location in order to improve the current solution using the following equation:

(9) 
$$X_{ij} = X_j^{min} + rand[0,1] * (X_j^{max} - X_j^{min})$$
  
The good position replaced the unimerved solution

The good position replaced the unimproved solution. Repeat Steps 2 – 4 until satisfied the stopping criteria.

# **Genetic Algorithm**

GA [4,19] is usually used in the solutions of the problems, which are hard or even impossible to be solved with conventional methods. Algorithm begins with a solution set which is referred to as population and represented by chromosomes at the beginning. The results which are obtained from this population are used to create a new population which is expected to include better solutions than the previous one. The solutions are chosen to create the new population according to their compatibility. This is due to the fact that the compatible ones will produce better results. This process is continued until a certain condition (for example, development of certain number of societies or the best solution) is maintained.

The process that GA undergoes until it comes to a solution can be described as coding the solution set, creating the initial population, assessing the compatibility of the solutions in the population, choosing the progenitor individuals according to the compatibility and creating new individuals through crossover and mutation processes. As for the control parameters of the GA, the crossover rate and the mutation rate are selected between 0.5-1.0 and 0.0001-0.05, respectively [20-23].

## Applying genetic algorithm to the problem

At first, numbers as much as one less than the number of elements in random NG set (remaining one being reference bus) which enables the constraint in (10) are designated for PG,n values that are output powers of the generation units in order to show bn number of bits (solution sensitivity).

(10) 
$$0 \le P_{Gn} \le 2^{bn} - 1, \ n \in N_G$$

Since these designated numbers can get a value out of current constraints of the generation units in the system, they are tailored towards constraints by mapping according to the following equation:

(11) 
$$P_{G,n}^{new} = P_{G,n}^{min} + \frac{P_{G,n}^{max} - P_{G,n}^{min}}{2^{bn} - 1} P_{G,n}^{init}, n \in N_G$$

There by, the inequality constraints given in Eq. (2) have been automatically provided. In this case, solutions that satisfy the condition below are taken as the solution.

(12)  $CP_{load}P_{load} < \sum_{n \in N_G} P_{G,n} < P_{load}$ Therefore, each created individual becomes a solution of the current problem.

# Hybrid Algorithm GA/ABC

This section presents hybridization between two metaheuristic algorithms, the genetic algorithm and the artificial bee colony algorithm, whose goal is to escape local minima and build a more efficient algorithm for the global optimization of non-convex functions. The mechanism of the hybridization between the two algorithms (GA and ABC) is given by Figure 1.

### **Results and analysis**

In this section, we will test and simulate the proposed algorithm on three standard networks of different sizes, the first of three generating units, the second of six generating units and the last of ten generating units. Our objective is to test the validity and efficiency of the proposed algorithm.

A. Test system 1

The first test system consists of three generator units; the characteristic data of this test system is shown in appendix A.1.

The following tables show the simulation results of threeunit generator. The first table presents the simulation by an AG, the second table gives the simulation by a bee colony algorithm while the hybridization of the two algorithms mentioned above is presented in the third table.



Fig.1. The hybrid Algorithm (GA/ABC)

Table1. Optimum results for three-unit-generator using AG

N PD	400(MW)	500(MW)	600(MW)	700(MW)
Unit	. ,	. ,	. ,	. ,
P <sub>1</sub> (MW)	77.3504	98.2479	114.1880	179.8718
P <sub>2</sub> (MW)	176.1905	193.3810	257.0000	262.8471
P <sub>3</sub> (MW)	154.0452	220.2552	246.0989	281.0830
F⊤ (\$/h)	20812	25482	30334	35484
$P_{L}(MW)$	7.5681	11.9144	17.3039	23.7677

Table2. Optimum results for three-unit-generator using ABC

✓ PD	400(MW)	500(MW)	600(MW)	700(MW)
Unit				
P <sub>1</sub> (MW)	82.0783	105.8799	130.0210	154.5139
P <sub>2</sub> (MW)	174.9937	212.7279	250.8461	289.3596
P <sub>3</sub> (MW)	150.4961	193.3066	236.4369	279.8949
F⊤ (\$/h)	20812	25465	30334	35424
P <sub>L</sub> (MW)	7.5681	11.9144	17.3040	23.7680

Table3. Optimum results for three-unit-generator using hybrid AG/ABC

PD	400(MW)	500(MW)	600(MW)	700(MW)
Unit				
P₁(MW)	82.0785	105.8801	130.0212	154.5141
$P_2(MW)$	174.9940	212.7282	250.8465	289.3600
P₃(MW)	150.4966	193.3071	236.4374	279.8950
F⊤ (\$/h)	20812	25465.5	30334	35424
P <sub>L</sub> (MW)	7.5682	11.9144	17.3041	23.7681

The following figures show the variation of the active powers, the active losses as well as the cost of fuel for different powers requested.

Table4. ED Comparison of the results for test system 1  $(P_D=400MW)$ 

	(AG/ABC)	GA [24]	PSO [24]	FPA [25]
F⊤(\$/h)	20812	20840.1	20838.3	20838.1
P <sub>L</sub> (MW)	7.5682	7.41324	7.41173	7.4126



Fig.3. Variation of the optimal powers obtained by ABC Algorithm



Fig.4. Variation of the optimal powers obtained by AG/ABC hybridization



Fig.5. Convergence characteristic of fuel cost- $P_D$ =400MW



Fig.6. Comparison of the fuel costs obtained by the three proposed algorithms

#### В. Test system 2

This test system consists of six thermal units whose characteristics are shown in Table A2. The simulation results are well classified in the following tables.

PD	700(MW)	800(MW)	900(MW)	1000(MW)
Unit				
P1(MW)	34.2637	29.7985	55.2137	37.7741
P2(MW)	19.9487	10.6154	43.3077	36.5299
P3(MW)	142.1795	130.8584	135.9158	191.3614
P4(MW)	96.4103	158.8889	171.5812	175.3419
P5(MW)	214.8095	257.9524	316.5238	319.4762
P6(MW)	211.8107	237.1905	218.4457	278.9951
FT (\$/h)	37004	41918	47276	52421
P <sub>L</sub> (MW)	19.4317	25.3306	31.9875	39.4812

Table5. Optimum results for six-unit-generator using AG

Table6. Optimum results for six-unit-generator using ABC

─_ PD	700(MW)	800(MW)	900(MW)	1000(MW)
Unit				
P <sub>1</sub> (MW)	28.2955	32.5863	36.8471	41.1656
P <sub>2</sub> (MW)	10.0000	14.4839	21.0773	27.7789
P <sub>3</sub> (MW)	118.9667	141.5434	163.9265	186.5622
P <sub>4</sub> (MW)	118.6801	136.0456	153.2196	170.5789
P <sub>5</sub> (MW)	230.7553	257.6676	284.1610	310.8290
P <sub>6</sub> (MW)	212.7338	243.0041	272.7569	302.5676
F <sub>T</sub> (\$/h)	36912	41896.7	47045.3	52361
P <sub>L</sub> (MW)	19.4315	25.3310	31.9884	39.4822

Table7. Optimum results for six-unit-generator using AG/ABC hybridization

✓ PD	700(MW)	800(MW)	900(MW)	1000(MW)
Unit				
P <sub>1</sub> (MW)	28.2891	32.8553	36.8568	41.1653
P <sub>2</sub> (MW)	10.0000	14.4829	21.0779	27.7783
P <sub>3</sub> (MW)	118.9393	141.5392	163.9111	186.5575
$P_4(MW)$	118.6832	136.5392	153.2137	170.5796
P <sub>5</sub> (MW)	230.7863	257.6753	284.2227	310.8203
P <sub>6</sub> (MW)	212.7354	243.0001	272.7074	302.5825
F⊤(\$/h)	36912	41897	47045.3	52361
P <sub>L</sub> (MW)	19.4322	25.3311	31.9885	39.4825





hybridization



Fig.9. Convergence characteristic of fuel cost-PD=900MW



Fig.10. Comparison of the fuel costs obtained by the three proposed algorithms

The variation of the active powers, the transmission losses and the fuel cost are presented as follows:

Table8. ED Comparison of the results for test system 2 (P<sub>D</sub>=900MW)

	(AG/ABC)	Ref [26]	Ref [27]
F <sub>⊤</sub> (\$/h)	47045.3	47326.100	47326.100
P <sub>L</sub> (MW)	31.9885	38.2782	38.2782

#### C. Test system 3

Ten-unit generator units characterize the last test system. The inputs data for this system is shown in Table A3. Table9. Optimum results for ten-unit-generator using AG

÷.,	Tablee: Optimum results for ten unit generater asing //o							
	PD	1000(MW)	1500(MW)	2000(MW)	2100(MW)			
	Unit							
	P₁(MW)	26.7993	13.3956	54.8284	54.7724			
	P <sub>2</sub> (MW)	36.7204	67.2967	70.5157	70.7756			
	P₃(MW)	47.0000	95.5419	90.3550	98.3489			
	$P_4(MW)$	34.8786	94.8645	120.8496	130.0000			
	P <sub>5</sub> (MW)	P <sub>5</sub> (MW) 50.0000 P <sub>6</sub> (MW) 70.0000		138.5476 107.3202	84.8207 208.4831			
	P <sub>6</sub> (MW)							
	P <sub>7</sub> (MW)	130.1955	174.5201	292.4550	269.5487			
	P <sub>8</sub> (MW)	127.7821	269.5165	337.4731	337.6334			
	P₀(MW)	254.1330	377.6398	431.6591	470.0000			
	P <sub>10</sub> (MW)	243.4976	313.5556	440.4948	468.6087			
	F⊤(\$/h)	54714	81973	112430	120060			
	P∟(MW)	21.0055	49.1144	84.4075	92.9913			
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Table10. Optimum results for ten-unit-generator using ABC

N PD	1000(MW)	1500(MW)	2000(MW)	2100(MW)
Unit	. ,	. ,		. ,
P <sub>1</sub> (MW)	26.8582	47.9273	54.6349	54.8882
P <sub>2</sub> (MW)	36.7748	62.1954	70.2732	70.8867
P <sub>3</sub> (MW)	47.0000	67.8841	91.2892	97.4483
P <sub>4</sub> (MW)	34.9505	58.8771	82.4041	123.5087
P <sub>5</sub> (MW)	50.0000	50.0000	155.4137	124.8430
P <sub>6</sub> (MW)	70.0000	70.0000	122.2683	192.1140
P <sub>7</sub> (MW)	129.9827	206.3168	286.0038	299.8007
P <sub>8</sub> (MW)	127.8603	225.5607	329.8019	319.4159
P₀(MW)	254.7783	378.2063	465.2065	442.0308
P <sub>10</sub> (MW)	242.7993	382.1324	427.5641	467.3199
F⊤(\$/h)	54714	81113.4	112420	120005
P <sub>L</sub> (MW)	21.0030	49.1001	84.6531	92.2552

Table11. Optimum results for ten-unit-generator using AG/ABC hybridization

nyphuization				
PD	1000(MW)	1500(MW)	2000(MW)	2100(MW)
Unit				
P <sub>1</sub> (MW)	26.8756	47.9566	54.3468	54.9971
$P_2(MW)$	36.8604	62.0888	70.2822	79.9619
P <sub>3</sub> (MW)	47.0000	68.1267	113.3810	112.2177
P <sub>4</sub> (MW)	34.8884	58.9161	114.3711	129.1988
P <sub>5</sub> (MW)	50.0000	50.0000	125.7714	160.0000
P <sub>6</sub> (MW)	70.0000	70.0000	116.1171	127.9126
P <sub>7</sub> (MW)	129.7875	206.9079	273.5031	299.9747
P <sub>8</sub> (MW)	128.3523	223.5997	326.3908	303.4561
P <sub>9</sub> (MW)	254.3386	376.8672	464.1116	458.4140
P <sub>10</sub> (MW)	242.8982	384.6615	426.1521	469.7628
F <sub>⊤</sub> (\$/h)	54714	81113.4	112260	119498
P <sub>L</sub> (MW)	21.0000	49.1234	84.4262	92.8946



Fig.11. Convergence characteristic of fuel cost-P<sub>D</sub>=2000MW

The comparison of the fuel costs obtained by the three algorithms is as follows:



Fig.12. Comparison of the fuel costs obtained by the three proposed algorithms

Table12.	ED	Comparison	of	the	results	for	test	system	3
(PD=2000	DMW)							•	

	(AG/ABC)	FPA [25]	ABC_PSO [28]	NSGAII [29]
P∟(MW)	84.6531	84.3	84.1736	84.25

To test and simulate the convergence of the hybrid algorithm, we changed the requested power at different levels for the three system test networks.

The proposed hybrid algorithm gives us a good result compared to the other basic algorithms AG, PSO and ABC, regarding losses and production cost.

Taking the test system network of three generator units (Table 4), for a power demand of 400 MW, a difference of 28.1 (h, 26.3 (h) and 26.1 (h) between (AG /ABC) and the GA reference [24], PSO [24] and the FPA reference [25] respectively.

Table A.1. Three-unit generator characteristics

Unit	a <sub>i</sub> (\$/MW²h)	b <sub>i</sub> (\$/MWh)	c <sub>i</sub> (\$/h)	e <sub>i</sub> (\$/h)	<i>f</i> i(rad/MW)	Pi <sup>min</sup> (MW)	P <sub>i</sub> <sup>max</sup> (MW)
1	0.03546	38.30553	1243.5311	300	0.0315	35	210
2	0.02111	36.32782	1658.5696	200	0.042	130	325
3	0.01799	38.27041	1356.6592	150	0.063	125	315

Table A.2. six-unit generator characteristics.							
Unit	a <sub>i</sub> (\$/MW <sup>2</sup> h)	b <sub>i</sub> (\$/MWh)	c <sub>i</sub> (\$/h)	e <sub>i</sub> (\$/h)	f <sub>i</sub> (rad/MW)	P <sub>i</sub> <sup>min</sup> (MW)	P <sub>i</sub> <sup>max</sup> (MW)
1	0.1525	38.540	756.800	300	0.031	10	125
2	0.1060	46.160	451.325	200	0.042	10	150
3	0.0280	40.400	1050.000	150	0.063	35	225
4	0.0355	38.310	1243.530	150	0.063	35	210
5	0.0211	36.328	1658.570	150	0.063	130	325
6	0.0180	38.270	1356.660	150	0.063	125	315
Table A.3. Ten-unit generator characteristics.							
Unit	a <sub>i</sub> (\$/MW <sup>2</sup> h)	b <sub>i</sub> (\$/MWh)	c <sub>i</sub> (\$/h)	e <sub>i</sub> (\$/h)	f <sub>i</sub> (rad/MW)	P <sub>i</sub> <sup>min</sup> (MW)	P <sup>max</sup> <sub>i</sub> (MW)
1	0.12951	40.5407	1000.403	33	0.0174	10	55
2	0.10908	39.5804	950.606	25	0.0178	20	80
3	0.12511	36.5104	900.705	32	0.0162	47	120
4	0.12111	39.5104	800.705	30	0.0168	20	130
5	0.15247	38.539	756.799	30	0.0148	50	160
6	0.10587	46.1592	451.325	20	0.0163	70	240
7	0.03546	38.3055	1243.531	20	0.0152	60	300
8	0.02803	40.3965	1049.998	30	0.0128	70	340
9	0.02111	36.3278	1658.569	60	0.0136	135	470
10	0.01799	38.2704	1356.659	40	0.0141	150	470

For the test system network of six generator units (comparison table 8), for a requested power of 900 MW, a slight difference of 280.8 (\$/h) between the proposed algorithm and references [26] and [27].

At the end the table of comparison of the production costs of a test network of ten generator units for a requested power of 2000 MW, a difference of 950 (\$/h), 1000 (\$/h) and 1119 (\$/h) h) between (AG/ABC) and the FPA reference [25], ABC\_PSO [28] and the NSGAII reference [29] respectively.

The results found by the hybrid algorithm affirm the convergence of the method in the field of electrical energy.

Hybridization of meta-heuristic methods is now opening wide application in several fields.

# Conclusion

This article proposes a new approach to solve the ED problem with valve point effect using a hybrid optimization algorithm of the two meta-heuristic methods such as the genetic algorithm and the bee colony.

As a first step we only applied the genetic algorithm on test systems of three, six and ten generator units. In the second step, another algorithm is applied to solve the economic dispatch problem such as the bee colony. The last algorithm is a hybrid algorithm that brings together the two algorithms mentioned above, the purpose of which is to minimize the cost of fuel and the transmission losses.

The comparison of the results with other methods reported in the literature shows the superiority of the proposed method and its potential to solve ED problems taking into account valve point effect. The AG/ABC algorithm can generate an efficient solution with high quality and more stable convergence characteristics than the genetic algorithm and the bee colony algorithm.

**Authors**: B. Naama, dr University of Science and Technology of ORAN ,Faculty of Electrical Engineering, Algeria, E-mail: naamasabah@yahoo.fr

K.Dahmani, Ph.D. Student, LDDEE Laboratory, Faculty of Electrical Engineering, Department of Electrotechnical Engineering University of Science and Technology of Oran Mohamed BOUDIAF, Algeria; E-mail: kawdahmani796@gmail.com

A.Abrouche, Ph.D. Student, LDDEE Laboratory, Faculty of Electrical Engineering, Department of Electrotechnical Engineering University of Science and Technology of Oran Mohamed BOUDIAF, Algeria; E-mail: amel.abrouche@outlook.com

H.Bouzeboudja, Prof.dr. University of Science and Technology of ORAN ,Faculty of Electrical Engineering, Algeria, E-mail: hbouzeboudja@yahoo.fr.

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