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MULTI-OBJECTIVE ECONOMIC EMISSION DISPATCH SOLUTION USING HYBRID MONKEY ALGORITHM

Naas KHERFANE[1], Fouad KHODJA[2], Riad Lakhdar KHERFANE[3], Mimoun YOUNES[4]
Samir KHERFANE[5], Abderrahmane AMARI[5]

[1] Faculté of technology, University Saad Dahleb Blida1 09000Algeria
, [2] Faculté of technology, University Saad Dahleb Blida1 09000Algeria
[3]University of Kasdi Merbah Ouargla 30000 Algeria
[4] University Djilali Lyabes Sidi Belabès 22000 Algeria
[5] University Ziane Achour Djelfa 17000Algeria

Abstract:

The main contribution of this paper is the application of the technique of hybridization between two meta-heuristics methods, PSO and MA, for solving the problem of economic and environmental dispatching, which is a multi-objective problem. The two contradictory objectives: fuel costs and emissions must be minimized at the same time while satisfying certain constraints of the system. In a multi objective optimization problem, to obtain good solutions, the concept of Pareto dominance is used to generate and sort dominated and non-dominated solutions. Several optimization runs of the proposed approach have been carried out on the IEEE 30 bus and a system with 6 generators. The strength of the proposed approach is tested and validated by solving several cases as: the fuel cost minimization, emission minimization, emission and cost minimization simultaneously

Keywords: Economic power dispatch (EPD) ,Combined economic emission dispatch (CEED),Monkey algorithm (MA),Particle Swarm Optimization (PSO),Hybrid method.

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

Applications of conventional optimization techniques such as the Gradient-based Algorithms are not adequate to solve this problem .

The Meta-heuristic techniques seem to be promising and evolving, and have come to be the most widely used tools for solving EPD.

To solve this problem, we have combined two meta-heuristic methods, the PSO and the MA. The acceleration of convergence speed, the improved solution quality and the balance between exploration and exploitation are achieved with approach PSO-MA.

2. PROBLEM FORMULATION

2.1. CONVENTIONNEL 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

2.2. OBJECTIVE FUNCTIONS

2.2.1. MINIMIZATION OF FUEL COST

The total fuel cost function is formulated as follows:

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

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

Where $f(P_G)$ is the total production cost in *$/hr*;
$f_i(P_{Gi})$ is the fuel cost function of unit *i* in *$/hr*;
a_i ,b_i and c_i are the fuel cost coefficients of unit *i*;
P_{Gi} is the real power output of unit *i* in *MW*;

2.2.3. 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:

$$P_L = \sum_{k=1}^{nl} g_k \left[V_i^2 + V_j^2 - 2V_iV_j \cos(\alpha_i - \alpha_j) \right] \quad (3)$$

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.

2.2.4 MINIMIZATION OF TOTAL EMISSION COST

The most important emissions considered in the power generation industry due to their effects on the environment are Sulfur Dioxide (SO_2) and Nitrogen Oxides (NO_x). These emissions can be modelled through functions that associate emissions with power production for each unit: [14]:

$$E(P_G) = \sum_{i=1}^{N_g} \left(\alpha_i P_{Gi}^2 + \beta_i P_{Gi} + \gamma_i \right) + \varepsilon_i \exp(\lambda_i P_{Gi}) \quad (4)$$

Where: α_i , β_i , γ_i , ε_i and λ_i are coefficients of the i^{th} generator emission characteristics

The bi-objective combined economic emission dispatch problem is converted into single optimization problem by introducing price penalty factor h:

$$\min F_B = \beta \sum_{i=1}^{Ng} f_i(P_{Gi}) + (1-\beta) h_i \sum_{i}^{Ng} E(P_{Gi}) \quad (5)$$

Where β is a weighting factor that satisfies $0 \le \beta \le 1$.

Where h_i:

$$h_i = \frac{\sum_{i}^{Ng} f(P_{Gi}^{\max})}{\sum_{i}^{Ng} E(P_{Gi}^{\max})} \quad (6)$$

3. PSO (PARTICLE SWARM OPTIMIZATION)

The PSO is a stochastic technique based on the population of optimization developed by Dr. Eberhart and Dr. Kennedy, inspired by the social behavior of the birds being assembled [12],[13].

The PSO algorithm searches in parallel using a group of individuals similar to other heuristic optimization techniques. In n-dimensional search space, the position and velocity of individual i are represented as the vectors $X_i = (x_{i1}, \dots, x_{in})$ and $V_i = (v_{i1}, \dots, v_{in})$ in this algorithm.

Let $Pbest_i = (x_{i1}^{Pbest}, \dots, x_{in}^{Pbest})$ and $Gbest_i = (x_1^{Gbest}, \dots, x_n^{Gbest})$ be the best position of individual i and its neighbors' best position so far, respectively. The modified velocity of each particle can be computed using the current velocity and the distance from *Pbest* and *Gbest*

The positions are modified using (8).

$$V_i^{k+1} = \omega V_i^k + c_1 rand_1 \times (Pbest_i^k - X_i^k) + c_2 rand_2 \times (Gbest^k - X_i^k) \quad (7)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (8)$$

V_i^k velocity of individual i at iteration k,

ω weight parameter,

c_1 , c_2 acceleration coefficients,

$rand_1, rand_2$ random numbers between 0 and 1,

X_i^k position of individual i at iteration k,

$Pbest_i^k$ best position of individual i until iterationk,

$Gbest^k$ best position of the group until iteration k.

The constants c_1 and c_2 represent the weighting of the stochastic acceleration terms that pull each particle toward the *Pbest* and *Gbest* positions.

Inertia weight factor that controls the exploitation and exploration of the search space by dynamically adjusting the velocity and it is computed using (9)

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{Iter_{max}} \times Iter \quad (9)$$

Where, $Iter_{max}$ is maximum iteration number and *Iter* is current iteration number.

Detailed pseudo-code as fellow [15]

1-A population of agents is created randomly.

$$X_i = (P_1, P_2, \dots \dots \dots, P_N)$$

2-Evaluate each particle's position according to the objective function

3-Cycle = 1

4-Repeat

5-Update the velocity of the particles

$$V_i^{k+1} = \omega V_i^k + c_1 rand_1 \times (Pbest_i^k - X_i^k) + c_2 rand_2 \times (Gbest^k - X_i^k)$$

6-Evaluate the velocity to ascertain if it is the range of $v_{max} \leq v_i \leq v_{min}$

7-Move particles to their new position

$X_i^{k+1} = X_i^k + V_i^{k+1}$

8- Evaluate to ensure that limits have not been exceeded.

9. Evaluate the fitness of the individual particle ,

9. Keep track of the individual's highest fitness (*Gbest*)

10. Modify velocities based on *Pbest* and *Gbest* position

11-Check if stopping criterion has been met. If not update the cycle and go to step (5).

12-End when the stopping criterion is met.

4. MA (MONKEY ALGORITHM) :

The MA was invented by Mucherino and Seref in 2007 [16]. MA is a meta-heuristic approach for global optimization [17-18], the concept of MA looks to strategies from other meta-heuristic methods like Genetic Algorithms, Differential Evolution, Ant Colony Optimization and etc. .[19]. It resembles the behaviour of ant in its search for food. The ant wanders randomly until it finds the food source, then it returns to the nest, laying a pheromone trail same. Upon climbing down the tree, the monkey marks tree branches with respect to the quality of the food available in the sub tree starting at that branch. When the monkey climbs up the tree again later, using the previous marks on the branches, it tends to choose those branches that lead to the parts of the tree with better quality of food [19], [20]:

Step 1. Define the objective function and the decision variables. Input the system parameters and the boundaries of the decision variables. The population size of monkeys (M), the climb number (N), for our case the optimization problem is of minimize the total fuel cost function (eq 6).

Step 2. first the initial positions of monkeys *i, i = 1; 2;….; M*, respectively, are randomly generated, with *n* dimension:

$$x_i = (x_{i1}, x_{i2}, ..., x_{in}) \qquad i = 1,2,..., M$$

Step 3. Climb process. Climb process is a step by step procedure to change the monkeys' positions from the initial positions to new ones that makes an improvement in the objective function. The climb process is as follows:

3-1. A vector is generated randomly as:

$$\Delta x_i = (\Delta x_{i1}, \Delta x_{i2}, ..., \Delta x_{in}), \quad i = 1,2,..., M \qquad (10)$$

$$\Delta x_{ij} = \begin{cases} +a & p(+a) = 0.5 \\ -a & p(-a) = 0.5 \end{cases} \qquad (11)$$

in which a is called the step length of the climb process.

3.2. Calculate the pseudo- gradient of the objective function *f* at point x_i.

$$f_{ij}^{'} = \frac{f(x_i + \Delta x_i) - f(x_i - \Delta x_i)}{2\Delta x_{ij}}, \; j = 1,2,..., n \quad (12)$$

$$f_{ij}^{'} = f_{ij}^{'} = \left(f_{i1}^{'}(x_i), f_{i2}^{'}(x_i), ..., f_{in}^{'}(x_i)\right) \qquad (13)$$

3.3. Define parameter $y = (y_1, y_2, ..., y_n)$ which is calculated as follows:

$$y_i = x_{ij} + a.sign\left(f_{ij}^{'}(x_i)\right) \qquad j = 1,2,..., n \qquad (14)$$

If $y = (y_1, y_2, ..., y_n)$ is feasible, then x is replaced by y_i

Otherwise x_i remains unchanged. The steps 3-1 to 3-3 are repeated until there is no considerable changes on the values of objective function or the climb number *N* reached.

Step 4. Watch-Jump process: After the climb process, each monkey arrives at its own mountaintop, therefore; each monkey will look around to find a higher mountain. If a higher mountain is found, the monkey will jump there. For this a parameter *b* is defined as eyesight of the monkey which is the maximal distance that the monkey can watch. The monkey jumps based on the following steps:

4-1. A real number of y is generated randomly in the range

$$y \in (x_{ij} - b, x_{ij} + b) \qquad j = 1,2,...,n \qquad (15)$$

4-2. If y is feasible and $f(y)$ is better than $f(x)$ for i^{th} monkey ($f(y) > f(x)$), the position is updated; otherwise, step 4-1 is repeated.

Step 5. The climb process is repeated by considering y as initial position.

Step 6. Somersault process: In this step, the monkeys find out new searching domains. Taking the centre of all the monkeys' positions as a pivot, each monkey will somersault to a new position forward or backward in the direction of pointing at the pivot. Based on the new position, the monkeys will keep on climbing. The somersault process is as follows:

6-1. First a somersault interval [c, d] is defined which the maximum distance that monkeys can somersault is. A real number is generated randomly within the somersault interval.

6-2. Defines parameter y as follows:

$$y_j = x_{ij} + \alpha(p_j - x_{ij}) \qquad (16)$$

$$p_j = \frac{1}{M}\sum_{i=1}^{M} x_{ij} \qquad j = 1,2,...,n \qquad (17)$$

where p is somersault pivot.

6-3. If $y = (y_1, y_2, ..., y_n)$ is feasible then x will be replaced by y, otherwise, repeat 6-1, 6-3 until a feasible y is found.

Step 7. Repeat steps 3-6 until the stopping criterion (maximum number of iteration) is met.

5. PSO-MA:

The balance between exploration and exploitation is achieved with approach PSO-MA. The searching process starts with the PSO, then the search is pursued by the MA, the results found by the PSO are used as starting points for MA, when the search stopped the final solution is reached. The following steps summarize description of the proposed algorithm:

Step 1. Run PSO

Step 2. Define the parameters of PSO and initialize particles

Step 3. Evaluate the fitness for each particle

Step 4. Update *Pbest* , *Gbest* values and the position and velocities of particles

Step 5. Check the stopping criteria

Step 5.1. If the stopping criterion is not satisfied go to step 3 else Communicate the solution found to MA and consider it as the initial research space.

Step 6. When the number of iterations is reached the search is stopped and the final result is displayed.

6. SIMULATION RESULTS:

The proposed PSO-MA 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, the electrical networks is tested and the result is compared .

6. 1. NETWORK 1: SYSTEM WITH 6 GENERATORS:

A standard IEEE 30-bus six-generator test system has been considered. This power system is connected through 41 transmission lines,total demand of 283.4MW. Fuel coefficients, Emissions coefficients of generators for IEEE 30-bus network are given in tables 1 and 2 [21]. The proposed approach has been applied to solve different cases without losses (table 3):

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}	0.05	0.5	10	200	100
P_{G2}	0.05	0.6	10	150	120
P_{G5}	0.05	1.0	20	180	40
P_{G8}	0.05	1.2	10	100	60
P_{G11}	0.05	1.0	20	180	40
P_{G13}	0.05	0.6	10	15	100

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Table 2:Power generation limits, emission coefficient data of generating units of 6-unit system.

Bus	α_i	β_i	γ_i	ε_i	λ_i
P_{G1}	0.06490	-0.05554	0.04091	0.0002	2.857
P_{G2}	0.05638	-0.06047	0.02543	0.0005	3.333
P_{G3}	0.04586	-0.05094	0.04258	0.000001	8.000
P_{G4}	0.03380	-0.03550	0.05326	0.002	2.000
P_{G5}	0.04586	-0.05094	0.04258	0.000001	8.000
P_{G6}	0.05151	-0.05555	0.06131	0.00001	6.667

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Tqble 3:Optimization results of PSO-MA approach for IEEE 30 bus

	Best (Cost) PSO-MA	Best (emission) PSO-MA	Best (cost, emission) MA	Best (cost, emission) PSO-MA
PG1 (MW)	0.108048	0.390952	0.256800	0.274945
PG2 (MW)	0.297429	0.460907	0.363300	0.363300
PG3 (MW)	0.525465	0.534422	0.519400	0.519400
PG8 (MW)	1.013721	0.392422	0.694900	0.694900
PG11(MW)	0.523147	0.544775	0.592528	0.539400
PG13(MW)	0.359106	0.512308	0.420100	0.420100
Fuel cost ($/h)	598.5404	637.2281	612.3962	605.0216
Emission (ton/h)	0.2221	0.1942	0.2013	0.2008
T(S)	10.92	10.6424	12.58	10.9076

6. Case 1: Quadratic fuel cost minimization

In this case the objective function is a quadratic form (equation 6); the fuel cost minimization decreased to 598.5404$/h in case 1 (Best Cost (PSO-MA)) in comparison to 637.2281 $/h in case 2 (Best emission (PSO-MA)) and in a same acceptable time which it is not very high(Table3)

The results obtained from the PSO-MA are compared with other methods reported in the literature. The results of this comparison are shown in Table 4. It can be seen that the minimum total obtained by this method is 598.540 $/h, which is less than the methods, BB-MOPSO [22] ,NSGA-II [22], NSGA [22] ,NPGA [22],SPEA [22],FCPSO[22], MBFA [23] ,FCPSO [23] ,SPEA [23],NPGA [23] ,NSGA [23],DE [23], MO-DE/PSO [24] BFGS-AL[28],NSGA-II[29],NSGA-RL[29]

Always from the results seen in the Tables, it is seen that the PSO-MA method can obtain lower fuel cost and lower emission level than the other mentioned methods.

In this case it is noticed, that the convergence was very fast because the number of the iteration of the latter towards optimal a solution was very small equal about 30. Fig.1

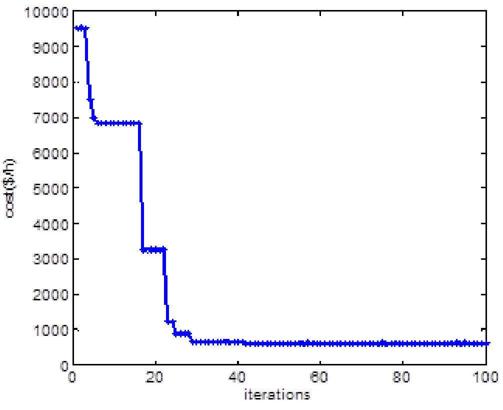

Fig.1. Convergence graph of PSO-MA, IEEE 30-bus test system (case1).

Table 4:Comparison of results by different algorithms for cost objective function of IEEE 30-bus system.
"Case minimization of cost"

Methods	P_{G1} (MW)	P_{G2} (MW)	P_{G3} (MW)	P_{G8} (MW)	P_{G11} (MW)	P_{G13} (MW)	Emission (T/h)	Cost ($/h)	T (S)
BB-OPSO [22]	0.109	0.3005	0.5234	1.017	0.5238	0.3603	0.22220	600.112	/
NSGA-II [22]	0.1059	0.3177	0.5216	1.0146	0.5159	0.3583	0.22188	600.155	/
NSGA [22]	0.1567	0.2870	0.4671	1.0467	0.5037	0.3729	0.22282	600.572	/
NPGA [22]	0.1080	0.3284	0.5386	1.0067	0.4949	0.3574	0.22116	600.259	/
SPEA [22]	0.1062	0.2897	0.5289	1.0025	0.5402	0.3664	0.22151	600.150	/
FCPSO [22]	0.1070	0.2897	0.525	1.015	0.5300	0.3673	0.22226	600.132	/
MO-E/PSO[24]	0.1078	0.304	0.5237	1.0147	0.5223	0.3616	0.22201	600.115	/
MBFA [23]	0.1133	0.3005	0.5202	0.9882	0.5409	0.3709	0.2200	600.17	/
FCPSO [23]	0.1070	0.2897	0.525	1.015	0.5300	0.3673	0.2223	600.13	/
SPEA [23]	0.1009	0.3186	0.5400	0.9903	0.5336	0.3507	0.2206	600.22	/
NPGA [23]	0.1116	0.3153	0.5419	1.0415	0.4726	0.3512	0.2238	600.31	/
NSGA [23]	0.1038	0.3228	0.5123	1.0387	0.5324	0.3241	0.2241	600.34	/
DE [23]	0.110	0.300	0.524	1.016	0.524	0.360	0.2231	600.11	/
BFGS-AL [28]	0.112442	0.302364	0.519194	1.018395	0.519193	0.362411	0.2221	600.1114	
NSGA-II [29]	0.1317	0.2713	0.5085	1.0066	0.5369	0.3790	0.2221	600.3220	
NSGA-RL [29]	0.0851	0.2855	0.5641	1.0114	0.5264	0.3618	0.2241	600.3285	
PSO-MA	0.1080	0.297429	0.525465	1.013721	0.523147	0.359106	0.2221	598.540	10.92

6. Case 2: Emission minimization

The objective function selected was the total emission cost minimization E as defined in (equation 4). Total emission decreased to 0.1942 ton/h in case 2 in comparison to 0.2221 ton/h in case1 (Table 3). The results obtained from the PSO-MA are compared with other methods reported in the literature,
the comparison is shown in Table 5, it can be seen that our results is bests than the other methods.
It is clear that with the PSO-MA approach optimum solution is achieved within 45 itirations Fig.2

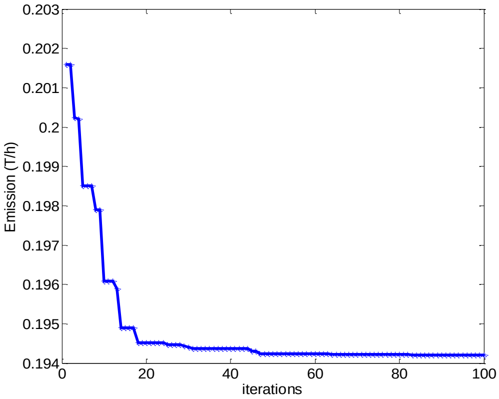

Fig.2. Convergence graph of PSO-MA, IEEE 30-bus test system (case2).

Table 5:Comparison of results by different algorithms for cost objective function of IEEE 30-bus system.
"case minimization of emissions"

Methods	P_{G1} (MW)	P_{G2} (MW)	P_{G3} (MW)	P_{G8} (MW)	P_{G11} (MW)	P_{G13} (MW)	Emission (T/h)	Cost ($/h)	T (S)
BB-MOPSO [222]	0.4071	0.4591	0.5374	0.3838	0.5369	0.5098	0.194203	638.262	/
NSGA-II [22]	0.4074	0.4577	0.5389	0.3837	0.5352	0.5110	0.19420	638.249	/
NSGA [22]	0.4394	0.4511	0.5105	0.3871	0.5553	0.4905	0.19435	639.209	/
NPGA [22]	0.4002	0.4474	0.5166	0.3688	0.5751	0.5259	0.19432	639.180	/
SPEA [22]	0.4116	0.4532	0.5329	0.3832	0.5383	0.5148	0.19421	638.507	/
FCPSO [22]	0.4097	0.4550	0.5363	0.3842	0.5348	0.5140	0.19420	638.358	/
MO-DE/PSO [24]	0.4061	0.4581	0.5408	0.3822	0.5376	0.5091	0.19420	638.270	/
MBFA [223]	0.3943	0.4627	0.5423	0.3946	0.5346	0.5056	0.1942	636.73	/
FCPSO [23]	0.4097	0.4550	0.5363	0.3842	0.5348	0.5140	0.1942	638.3577	/
SPEA [23]	0.4240	0.4577	0.5301	0.3721	0.5311	0.5190	0.1942	640.42	/
NPGA [23]	0.4146	0.4419	0.5411	0.4067	0.5318	0.4979	0.1943	636.04	/
NSGA [23]	0.4072	0.4536	0.4888	0.4302	0.5836	0.4707	0.1946	633.83	/
DE [23]	0.406	0.459	0.538	0.383	0.538	0.51	0.1952	638.27	/
BFGS-AL [28]	0.406074	0.459069	0.537939	0.382954	0.537939	0.510027	0.1942	638.2738	/
NSGA-II [29]	0.3463	0.4668	0.5448	0.4111	0.5642	0.5008	0.1955	633.0944	
NSGA-RL [29]	0.3842	0.4806	0.5226	0.3857	0.5456	0.5163	0.1953	638.1229	
PSO-MA	0.3909	0.46090	0.5344	0.3924	0.5447	0.51230	0.1942	637.2281	10.642

6. Case 3: Emission and cost minimization

In single-objective optimization there exists a global optimum, while in the multi-objective case no optimal solution is clearly defined but rather a set of optimums, which constitute the so called Pareto-optimal front (Gil et al, 2007).In this case, all constraints about fuel cost and pollution emission are considered. The CEED problem was considered as multi objective problem. The best compromise solution by using PSO-MA is given in Table 3. The fuel cost in this case is reduced by as much as 06.5 % in comparison to 637.2281$/h in case 2. The emission is reduced by as much as 14.36% in comparison to 0.2221 ton/ h in case 1. In this case, two competing objectives, fuel cost and emission were considered. This multi-objective optimization problem was solved by the proposed approach (PSO-MA).

Table 6

Comparison of results by different algorithms for cost objective function of IEEE 30-bus system.
"Compromise case minimization of emissions and cost"

Methods	P_{G1} (MW)	P_{G2} (MW)	P_{G3} (MW)	P_{G8} (MW)	P_{G11} (MW)	P_{G13} (MW)	Emission (T/h)	Cost ($/h)	T (S)
MODE [25]	28.2240	34.8305	51.7159	70.2157	53.2158	45.1981	0.2008	610.1436	/
NPGA [26]	0.2663	0.3700	0.5222	0.7202	0.5256	0.4296	0.2015	608.90	/
NSGA-II [25]	24.2651	40.2072	52.0703	69.3592	56.4003	41.0979	0.2011	609.7053	/
MOACSA [25]	23.1093	36.6487	54.1967	71.2708	54.7066	43.4679	0.2020	608.2403	/
BB-MOPSO [22]	0.2595	0.3698	0.5351	0.6919	0.5500	0.4277	0.20083	609.747	/
MOPSO [25]	26.3789	39.0007	54.6339	71.0841	52.5905	39.7120	0.2014	609.2164	/
MOPSO [27]	0.2516	0.3770	0.5283	0.7124	0.5566	0.4081	0.2017	608.65	/
BFGS-AL [28]	0.233439	0.361530	0.536481	0.747001	0.536482	0.419.67	0.2033	606.7985	/
NSGA-II [28]	0.3095	0.40557	0.6201	0.6875	0.4813	0.3305	0.2024	612.6105	
NSGA-RL [29]	0.2675	0.3729	0.5680	0.6222	0.5857	0.4181	0.2001	613.2044	
MA	0.256800	0.363300	0.519400	0.694900	0.592528	0.420100	0.2013	612.3962	/
PSO-MA	0.274945	0.363300	0.519400	0.694900	0.539400	0.420100	0.2008	605.0216	10.92

It is clearly shown that PSO-MA obtains the best cost and best emission compared to others. The best compromise solutions are given in Table 6. It is quite evident that the proposed PSO-MA approach yields satisfactory compromise solutions. Fig. 3 shows the relationship (tradeoff curve) of the fuel cost and emission objectives of non-dominated solutions. It is quite clear that these solutions found were well-distributed and covered the entire Pareto front of this case.

At first, fuel cost objective, emission objective are optimized individually to explore the extreme points of the tradeoff surface in all cases. In this case, the basic EPD has been implemented as the problem becomes a single-objective optimization problem.

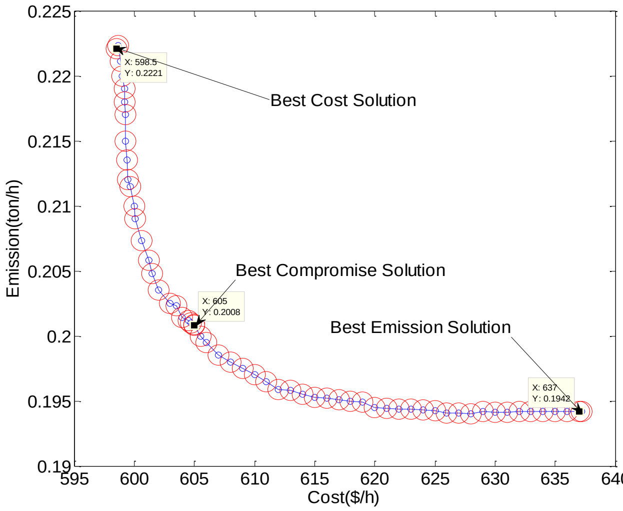

Fig.3. Pareto-optimal front of the proposed approach (case 3).

The proposed PSO-MA approach has been implemented to optimize cost and emission objectives simultaneously considering the third case stated above. The distribution of the Pareto-optimal set over the trade-off surface is shown in Fig.3 for the Case 3.

It can be seen that the proposed PSO-MA technique preserves the diversity of the no dominated solutions over the Pareto-optimal front and solve effectively the problem in the all case considered. It is worth mentioning that, the Pareto-optimal set has 44 no dominated solutions. Out of them, two no dominated solutions that represent the best cost and best emission are given in Table 3 and in fig 3. The experimental results show that the proposed method approach yields satisfactory compromise solutions, then 605.0216 ($/h) and 0.2008 (ton/h), the average CPU time in this case is found to be 10.90 s to arrive at a solution.

So we can say that the proposed PSO-MA technique is superior compared to all reported techniques, the simulation results also reveal the superiority of the proposed technique in terms of the diversity and quality of the obtained Pareto-optimal solutions Fig.4.

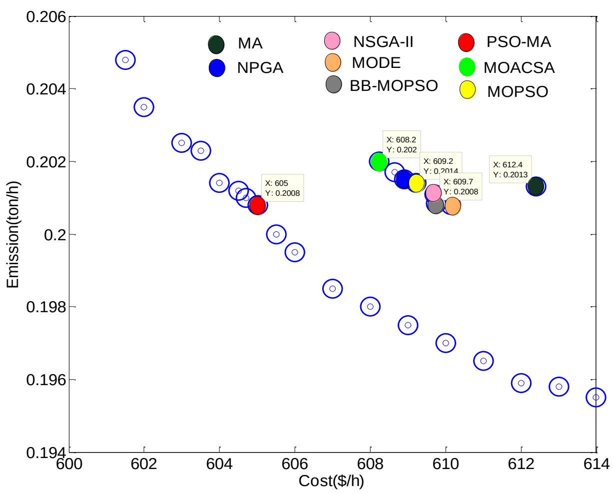

Fig. 4. the face of Pareto-optimal of the approach suggested

7.*CONCLUSION:*

The PSO-MA based approach presented in this paper was applied to EPD problem with competing objectives of minimization of fuel cost and pollutant emissions. The effectiveness of the proposed approach is investigated on the IEEE 30- test system with 6 generators.
.Reached results shows that this approach is efficient for solving multi-objective EPD problems where Pareto optimal solutions can be found in one simulation run. Compared with other methods in literature, the PSO-MA has better diversity characteristics, and yields better compromise solutions

8.Prospects:

In this contribution we have applied a hybridization technique between two metaheuristic methods, PSO and MA, to solve the problem of economic and environmental dispatching, which is a multi-objective problem. We hope that in the next work of other researchers to use the MA monkey algorithm by making other hybridizations with other swarm (firefly , frog leaping , ant lion …..etc) algorithms and to solve the multi-objective problem of dispatching by inserting other objectives and switch from a CEED Combined economic emission problem to a CHPEED Combined Heat Power Economic Emission Dispatch problem for example.

Références :

[1] Carpentier, J.,(1962). *Contribution a l'étude du dispatching économique. Bulletin de la Société Française des Electriciens, vol. 3, pp. 431–447.*
[2] Vanderbei, J.R and Shanno,F.D.,(1999). *An interior-point algorithm for nonconvex nonlinear programming. Comput. Optim. Appl., vol. 13, pp. 231–252.*
[3] Bottero,M.H., Caliana,E.D.and A. R., Fahmideh Vojdani., (1982). *Economic dispatch using the reduced*

hessian. IEEE Trans on Power Appra. Syst.,vol. 101, pp. 3679-3688.

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

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

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

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

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

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

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

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

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

[13] Eberhart RC and Kennedy J (1995), *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, pp. 39–43.*

[14] Yao, F., Dong, Z. Y., Meng, K., Xu, Z., Ho-Ching, Iu., et al. (2012). *Quantum-inspired particle swarm optimization for power system operations considering wind power uncertainty and carbon tax in Australia 2012. IEEE Transactions on Industrial Informatics, 8(4), 880–888.*

[15]Emmanuel Dartey Manteaw, Nicodemus Abungu Odero, December (2012),*Combined EconomicAnd Emission Dispatch solution Using ABC_PSO Hybrid Algorithm With Valve point Laoding Effect , International Journal of Scientific and Research Publications, Volume 2, Issue 12.*

[16] Liang Zheng, *An improved monkey algorithm with dynamic adaptation, Applied Mathematics and Computation 222 (2013) 645–657*

[17] Yuzhong Li , Improved Monkey-King *Genetic Algorithm for Solving Large Winner Determination in Combinatorial Auction, 2012 International Conference on Medical Physics and Biomedical Engineering, Physics Procedia 33 (2012) 1086 – 1092.*

[18] Carlos M. Ituarte-Villarreal, Nicolas Lopez and Jose F. Espiritu, *Using the Monkey Algorithm for Hybrid Power Systems Optimization, Conference Organized by Missouri University of Science and Technology 2012- Washington D.C, Procedia Computer Science 12 (2012) 344 – 349.*

[19] A. Mucherino, O. Seref, P.M. Pardalos, (2008) *"Simulating Protein Conformations through Global Optimization", November 19, 2008.*

[20] R.Q. Zhao, W.S. Tang,(2008) *Monkey algorithm for global numerical optimization, Journal of Uncertain Systems. 2 (3), 165–176.*

[21] Niknam T, Narimani MR, Jabbari M, Malekpour AR, (2011), *A modified shuffle frog leaping algorithm for multi-objective optimal power flow. Energy; 36:6420–32.*

[22]Yong Zhang, Dun-Wei Gong, Zhonghai Ding, (2012), *A bare-bones multi-objective particle swarm optimization algorithm for environmental/economic dispatch, Information Sciences 192, 213–227*

[23] P.K. Hota, A.K. Barisal, R. Chakrabarti, (2010), *Economic emission load dispatch through fuzzy based bacterial foraging algorithm, Electrical Power and Energy Systems 32 , 794–803*

[24] Dun-wei Gong, Yong Zhang, Cheng-liang Qi, (2010) *, Environmental/economic power dispatch using a hybrid multi-objective optimization algorithm, Electrical Power and Energy Systems 32 , 607–614*

[25] B. Srinivasa Rao, K. Vaisakh, (2013) , *Multi-objective adaptive Clonal selection algorithm for solving environmental/economic dispatch and OPF problems with load uncertainty, Electrical Power and Energy Systems 53 , 390–408*

[26] Rajesh Kumar, Abhinav Sadu, Rudesh Kumar, S.K. Panda, (2012) , *A novel multi-objective directed bee colony optimization algorithm for multi-objective emission constrained economic power dispatch, Electrical Power and Energy Systems 43 , 1241–1250*

[27] M.A. Abido, (2009) , *Multiobjective particle swarm optimization for environmental/economic dispatch problem, Electric Power Systems Research 79 , 1105–1113*

[28] El Hachmi Talbia,_, *Lhoussine Abaalia, Rachid Skourib, Mustapha El Mouddenc , (2020) , Solution of Economic and Environmental Power Dispatch Problem*

of an Electrical Power System using BFGS-AL Algorithm, Procedia Computer Science 170 857–862

[29] Teodoro Cardoso Bora, Viviana Cocco Mariani, Leandro dos Santos Coelho , (2019) Multi-objective optimization of the environmental-economic dispatch with reinforcement learning based on non-dominated sorting genetic algorithm , Applied Thermal Engineering, 146: 688– 700.