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Bi-objective Optimization Apply to Environmental and Economic Dispatch Problem Using the Method of Corridor Observations

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ABSTRACT:
This paper presents a proposed and applicable optimization algorithm based on the evolutionary algorithm to solve an environmental and economic Dispatch (EED) problem. This problem is seen like a bi-objective optimization problem where fuel cost and gas emission are objectives .in this method, the optimal Pareto front is found using the concept of corridor observation and the best compromised solution is obtained by fuzzy logic. The feasibility of this method is demonstrated using power systems with three generation units, and it is compared with the other evolutionary methods of Optimization Toolbox of Matlab in terms of solution quality and CPU time. The simulated results showed that the proposed method is indeed capable of obtaining higher quality solutions in shorter computational time compared to other evolutionary methods. In addition the other advantage is that our approach solves in the same time a unit commitment problem and it can use with n-generation units.

KEYWORDS: *bi-objective, corridor observations, Evolutionary algorithm, fuel cost, gas emission, optimal PARETO front, optimization*

I. INTRODUCTION

The economic dispatching (ED) is one of the key problems in power system operation and planning. The basic objective of economic dispatch is to schedule the committed generating unit outputs so as to meet the load demand at minimum operating cost, while satisfying all equality and inequality constraints. This makes the ED problem a large – scale highly constrained non linear optimization problem. In addition, the increasing public awareness of the environmental protection and the passage of the Clean Air Act Amendments of 1990 have forced the utilities to modify their design or operational strategies to reduce pollution and atmospheric emissions of the thermal power plant. Several strategies to reduce the atmospheric emissions have been proposed and discussed. These include: installation of pollutant cleaning equipment, switching to low emission fuels, replacement of the aged fuel-burners with cleaner ones, and emission dispatching. The first three options require installation of new equipment and/or modification of the existing ones that involve considerable capital outlay and, hence, they can be considered as long-term options. The emission dispatching option is an attractive short-term alternative in which the emission in addition to the fuel cost objective is to be minimized. Thus, the ED problem can be handled as a multi-objective optimization problem with non-commensurable and contradictory objectives. In recent years, this option has received much attention [1–5] since it requires only small modification of the basic ED to include emissions.

In the literature concerning environmental/economic dispatch (EED) problem, different technics have been applied to solve EED problem. In [1, 2] the problem was reduced to a single objective problem by treating the emission as a constraint. This formulation, however, has a severe difficulty in getting the trade-off relations between cost and emission. Alternatively, minimizing the emission has been handled as another objective in addition to the cost [5]. However, many mathematical assumptions have to be given to simplify the problem. Furthermore, this approach does not give any information regarding the trade-offs involved. In other research direction, the multi-objective EED problem was converted to a single objective problem by linear combination of different objectives as a weighted sum [3], [6]. The important aspect of this weighted sum method is that a set of non-inferior (or Pareto-optimal) solutions can be obtained by varying the weights. Unfortunately, this requires multiple runs as many times as the number of desired Pareto-optimal solutions. Furthermore, this method cannot be used in problems having a non-convex Pareto optimal front. To overcome it, certain method optimizes the most preferred objective and considers the other objectives as constraints bounded by some allowable levels [5]. The most obvious weaknesses of this approach are that, then are time-consuming and tend to observed weakly non-dominated solutions [5].

The other direction is to consider both objectives simultaneously as competing objectives. The recent review to the Unit Commitment and Methods for Solving [7] showed that evolutionary algorithms are the most used in this case; certainly because they can efficiently eliminate most of the difficulties of classical methods [5]**.** The major problems of these algorithms, is to find the pareto optimal front and to conserve the non-dominated solutions during the search. In this paper we perform and apply one optimization method proposed in [9] to solve the EED problem. The particularity of this method is based to the fact that the search of front and optimal Pareto is found by the concept of corridor, and the archives is dynamic. This dynamism reduce the loses of the non-dominated solution during the different generations. In the second part of this paper, we present materials and methods to solve the problem, and the third part, present simulation and results obtained.

II. MATERIALS AND METHODS

In this part, we formulate the EED problem and present our approach to solve it.

2.1. Problem formulation

The EED problem is to minimize two competing objective functions, fuel cost and emission, while satisfying several equality and inequality constraints. Generally the problem is formulated as follows :

2.1.1. Problem objectives

- Minimization of fuel cost

The generator cost curves are represented generally by quadratic functions. The total fuel cost ($/h) in terms of period T, can be expressed as:

$$F\left(p_{i,t}\right) = \sum_{t=1}^{T} \sum_{i=1}^{Ng} c_{fi}(p_{i,t}) I_{i,t} + ST_{i,t}(1 - I_{i,t-1}) I_{i,t} \tag{1}$$

Where

$$c_{fi}(p_{i,t}) = a_i + b_i p_{i,t} + c_i p_{i,t}^2 \tag{2}$$

and $c_{fi}(p_{i,t})$ is the generator fuel cost function; a_i, b_i and c_i are the cost coefficients of i^{th} generator; $P_{i,t}$, is the electrical output of i^{th} generator; Ng is the number of generators committed to the operating system ; $I_{i,t}$thestatut of differents generators ; ST_i the start-up cost .

- Minimization of gas emission

The atmospheric pollutants such as sulpher dioxides (SO_2) and nitrogen oxides (NO_X) caused by fossil-fueled thermal units can be modeled separately. However, for comparison purposes, the total emission (*ton/h)* in one period T of these pollutants can be expressed as:

$$E\left(p_{i,t}\right) = \sum_{t=1}^{T} \sum_{i=1}^{Ng} e_{fi}(p_{i,t}) I_{i,t} \tag{3}$$

where

$$e_{fi}(P_{i,t}) = (\alpha_i + \beta_i p_{i,t} + \delta_i p_{i,t}^2) \tag{4}$$

and α_i, β_i, δ_i are the emission coefficients of the i^{th} generator.

2.1.2. Objective constraints

- Power balance constraint

$$p_{load,t} - \sum_{i=1}^{Ng} p_{i,t} I_{i,t} = 0 \tag{5}$$

- Spinning reserve constraint :

$$p_{load,t} + R_t - \sum_{i=1}^{Ng} p_{\max,i} I_{i,t} \le 0 \tag{6}$$

- Generation limit constraints :

$$p_{\min,i} I_{i,t} \le p_{i,t} \le p_{\max,i} I_{i,t} \quad , i = 1 ...... Ng \tag{7}$$

- Minimum up and down time constraint :

$$I_{i,t} = \begin{cases} 1 \; if \; T_i^{on} \prec T_i^{up} \\ 0 \; if \; T_i^{off} \prec T_i^{down} \\ 0 \; or \; 1 \; otherwise \end{cases} \tag{8}$$

Where T_i^{up} represent the minimum up time of unit *i*; T_i^{down} the minimum down time of unit *i*T_i^{off} is the continuously off time of unit *i* and T_i^{on} the continuously on time of unit- *i* .

- Start-up cost

$$ST_i = \begin{cases} HST_i \; if \; T_i^{down} \le T_i^{off} \le T_i^{down} + T_i^{cold} \\ CST_i \; if \; T_i^{off} \succ T_i^{cold} + T_i^{down} \end{cases}$$

2.2. The proposed approach

2.2.1. Algorithm of corridors observations method

The different steps of the proposed approach to solve EED problem is summarize in the follow figure

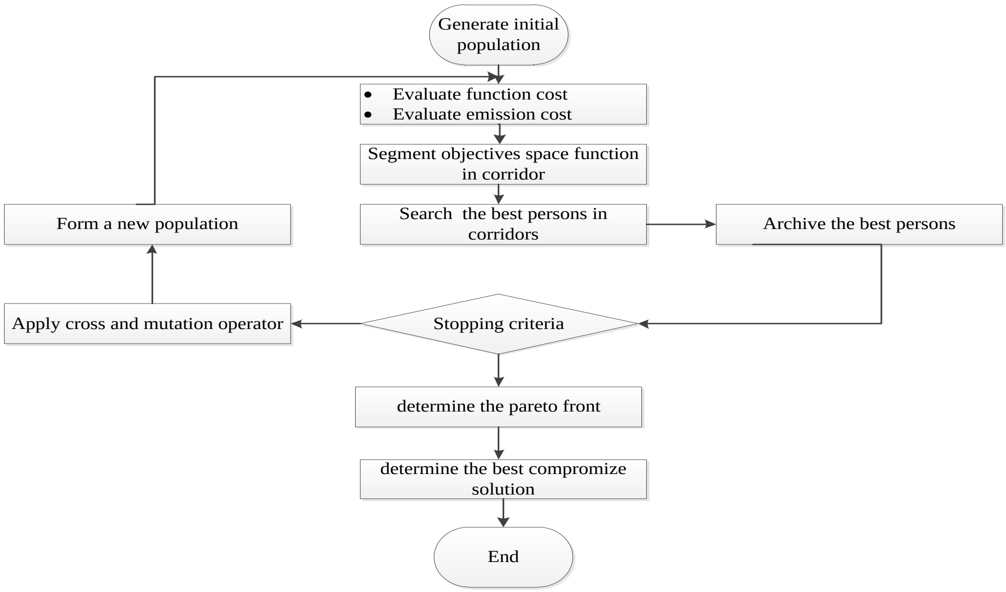

Figure 1: Different steps of the algorithms

- Step 1

In the first step, we start with to the status of different unit generation, were we create randomly the initial population. Each individual is a combination of each power generation unit

- Step 2

In the second, using equations (1) and (3) we evaluate the objective functions of this population

- Step 3

Using the minimum of the different objective functions of individuals who respect the constraints (5) to (8), we define the space solution and segment it to the corridors observation following the different axes which are specify by each function.

- Step 4

In each corridor, we search the best individual who have the minimum objectives functions, and the non feasible solutions are classified using the number and the rate of violation constraints. Those solutions will be used to increase the number of feasible solutions.

- Step 5

We keep in the archives those best individuals

- Step 6

We verify the stoping criteria define as [9] :

$$\xi = \ln(d) \tag{9}$$

where

$$d = \sum_{j=1}^{N_F} \left[\frac{1}{Cl} \sqrt{\sum_{i=1}^{cl} \left(\frac{F_{j,i}^{t} - F_{j,i}^{t-1}}{F_{\max} - F_{\min}} \right)} \right] \tag{10}$$

explain the metric progression of the best individuals in each corridor. N_F is the number of objectives functions ; Cl the number of corridor ; $F^t_{j,i}$, $F^{t-1}_{j,i}$ the j^{th} objective function of the best individual in i^{th} corridor ; F_{min} and F_{max} the minimum and maximum of the j function ; t is the present generation, t-1 the anterior generation. At times the maximum number of generation can be the alternative stopping criteria

- step 7

If the stopping criteria is not verified, we construct the new population using the selection ,cross and mutation operators apply to the archive population and we return to step 2.

- Step 8

If the stopping criteria is verified we find the best compromise solution among the individuals of the Pareto front. Due to imprecise nature of the decision maker's judgment, each objective function of the i-th solution is represented by a membership μ_i function defined as

$$\mu_i = \begin{cases} 1 \quad if \quad F_i \le F_i^{\min} \\ \dfrac{F_i^{\max} - F_i}{F_i^{\max} - F_i^{\min}} \quad F_i^{\min} \le F_i \le F_i^{\max} \\ 0 \quad if \quad F_i \ge F_i^{\max} \end{cases} \tag{11}$$

For each non-dominated solution, the normalized membership function is μ^k calculated as:

$$\mu^k = \frac{\sum_{i=1}^{N_F} \mu_i^k}{\sum_{k=1}^{M} \sum_{i=1}^{N_F} \mu_i^k} \tag{12}$$

where M is the number of non-dominated solutions. The best compromise solution is the one having the maximum of μ^k .

2.2.2. Implementation and strategy to search solution

To find the problem solution algorithm, we have to :

- Explore space solutions

During this step, the algorithm explore space solutions with using 0.9 percentage of random mutation operator and 0.1 percentage of uniform cross operator, it corresponding to the inequality $\varepsilon \ge -8$.

- Exploit space solutions

To exploit space solutions, the algorithm applied to the population random mutation a percentage of 0.9 and 0.1 percentage of arithmetic cross operator. it corresponding to the inequality $-18 \le \varepsilon \le -12$.

- Apply hybrid mode

It's a transition between exploration and exploitation which correspond to 0.5 percentage of cross probability and 0.5 percentage of mutation probability. The range of stopping criteria is: $-12 \le \varepsilon \le -8$

III. SIMULATION AND RESULTS

In order to validate the proposed procedure and to verify the feasibility of the corridor method to solve the EED, a 3-units generation system is tested [10] and extent to 6, 10 and 15 units génération. The proposed method is implemented with Matlab 2010.b on a core i3 2.1 GHz and the results are compared with other evolutionary algorithms (GA and GA multi-obj) of optimization tool. The data concerning the unit generation is given in table 1 to table 2 [10].

Table 1. The 3-units system data

Unit	P_i^{max} (MW)	P_i^{min} (MW)	a ($ /h)	b ($ /MWh)	c ($ /MW^{2}h)	R_i^{up} ($ /MW)	R_i^{down} ($ /MWh)
1	600	150	561	7.29	0.00156	100	100
2	400	100	310	7.85	0.00194	80	80
3	200	50	78	7.97	0.00482	50	50

Table 2. SO_2 and NOx coefficients emission gas data of 3-units

Units	α_{so2} (tons/h)	α_{Nox} (tons/h)	β_{so2} (tons/MWh)	β_{Nox} (tons/MWh)	δ_{so2} (tons/MW^{2}h)	δ_{Nox} (tons/MW^{2}h)
1	0,5783298	0,04373254	0,00816466	-9,4868099 e^{-6}	1,6103e^{-6}	1,4721848 e^{-7}
2	0,3515338	0,055821713	0,00891174	-9,7252878 e^{-5}	5,4658 e^{-6}	3,0207577 e^{-7}
3	0,0884504	0,027731524	0,00903782	-3,5373734 e^{-4}	5,4658 e^{-6}	1,9338531 e^{-6}

In the implementation, we add the different coefficients of each gas per groups to have the coefficient of the whole gas.

3.1 Achievement of Pareto front

The Pareto front is obtained, keeping the best individuals (individuals who have the minimum fuel cost are conserved in relation to the emission axes and vice versa) that respect all the contraints in each corridor during the evolution. To simulate the evolution of pareto front we have initialize the population size at 300 , the maximum generation at 1000 ,the number of corridor at 50 and load demand is 1000MW.

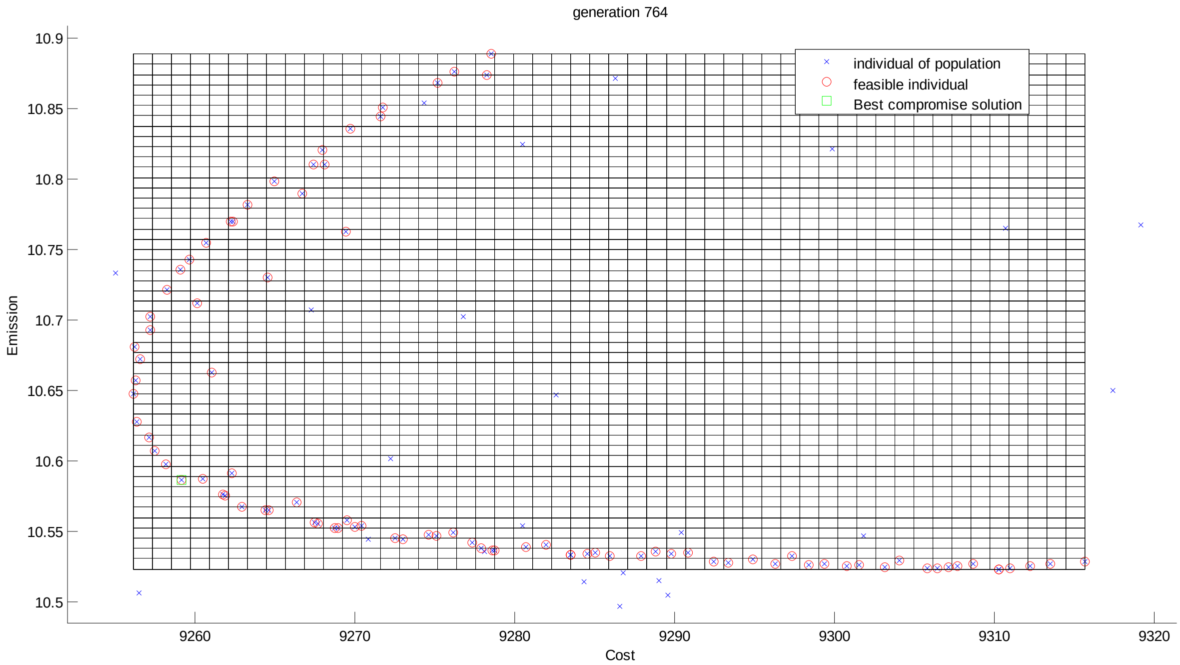

Figure 2 : Pareto optimal front at the end of process (1000MW load demand).

In the search of the best solution in each corridor, at the beginning the algorithm could not find the best feasible solutions but in the process of evolution the number of these solutions increases up to the Pareto optimal front.

3.1. Study of convergence

The curve convergence show that until one number of generations the algorithm finds the best solution, from this times gas emission and fuel cost is uniform. It expresses the performance of stopping criteria.

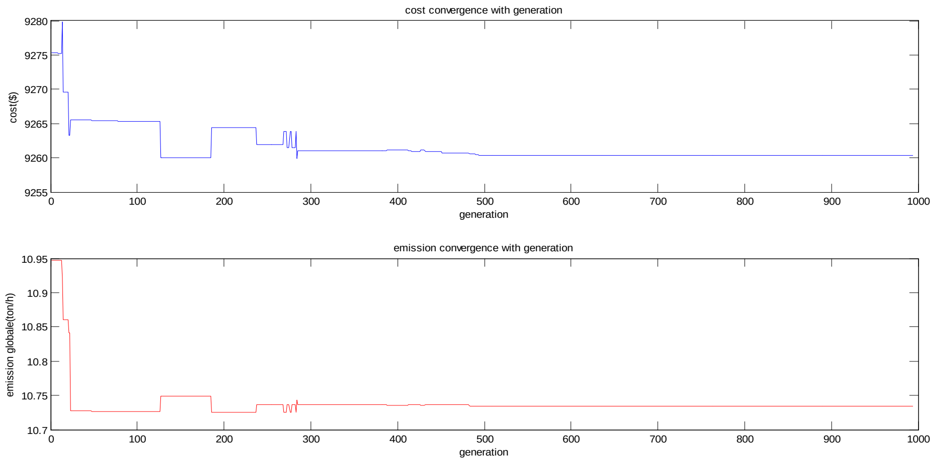

Figure 3: Convergence of fuel cost($) and gas emissions(ton/h) objective functions (1000MW).

3.2. Apply of method to 24 hours

To present the effectiveness of our approach to unit commitment and EED, we have apply it to plan the production of 3-units during 24 hours.

Table 3. Unit commitment and EED during 24 hours

Hours (H)	Demands (MW)	P1 (MW)	P2 (MW)	P3 (MW)	Fuel cost $X10^3$($)	Emission gas (ton/h)	Starting cost ($/MWh)	Total cost ($)
1	550	0	0	549.9	5.0415	5.6380		
2	600	0	0	599.9	5.4957	6.1468		
3	650	108.0382	0	541.8742	5.9646	6.6979	50	
4	700	114.5484	0	585.351	6.4169	7.2059		
5	750	150.228	0	599.67	6.8777	7.7323		
6	800	0	224.27	575.62	7.4424	8.5731	80	
7	850	0	250.314	599.58	7.8893	9.1188		
8	900	0	300.541	599.3621	8.3352	9.7188		
9	950	114.9563	239.4409	595.5072	8.8142	10.1626	50	
10	1000	128.8152	275.9956	595.0968	9.2607	10.7347		
11	1050	141.965	308.5501	599.3873	9.7144	11.3159		
12	900	0	300.03	599.8287	8.3342	9.7188		
13	850	0	250.0713	599.8287	7.8894	9.1184		
14	800	0	225.58	574.3207	7.4419	8.5747		
15	750	150.7585	0	599.1479	6.8779	7.7327	50	
16	700	114.5434	0	585.355	6.4116	7.2059		
17	650	108.0326	0	541.8732	5.9646	6.6979		
18	600	0	0	599.9	5.4957	6.1468		
19	730	130.2853	0	599.6148	6.6913	7.5171	50	
20	820	0	233.9595	585.9423	7.6209	8.7892	80	
21	860	0	260.1659	599.7343	7.9778	9.2361		
22	900	0	300.531	599.3721	8.3352	9.7188		
23	950	114.9553	239.4419	595.5072	8.8142	10.1626	50	
24	1000	128.8152	275.9956	595.0968	9.2607	10.7347		
Total					178.368		410	178778

In function of demand we see that some unit could be on and other off, to minimize the fuel cost and emission gas. The plan production of different units is represent in follow figure

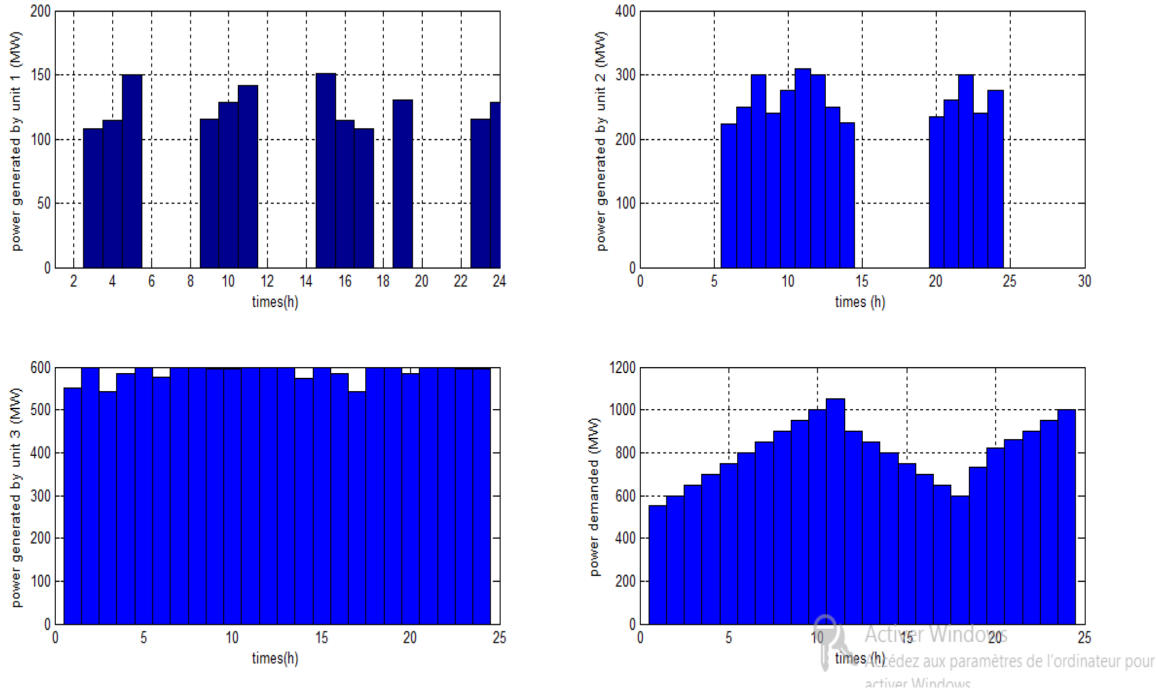

Figure 3: Production plan of different units

3.3. Comparison of results

To show the effectiveness of the proposed method, we have compared it with other evolutionary algorithm of optimization tool of matlab. The same parameter is considered and the criteria for comparisons are cost and average CPU times.

Tableau 4: Comparison methods with 1000MW of load demand

	GA	GA multi-obj.	corridor
P_1 (MW)	400.0587	399,999	598.4477
P_2 (MW)	399.9885	399,999	275.8265
P_3(MW)	199.9518	199,999	125.6293
Fuel Cost($ /h)	9879.2053	9878,988	9260,6
Emission ton/h	11.755	11,644	10.5768
Average CPU times	244.9135	261.9536	23.29854

This table show that our method is best in term of fuel cost and emission gas

3.4. Impact of numbers of units to fuel cost, gas emission and average CPU times

To show this impact, we have multiplied the number of units of our 3-units. The results are presented to follow table.

Tableau 5: Impact of numbers of units to fuel cost, gas emission and average CPU times

Number of units	3	6	10	15
Fuel cost($)	9.2606	9.1911	9.176	9.177
Gas emission(ton/h)	10.7347	10.2771	10.3679	10.3683
Average times(s)	23.29	31.92	49.40	104.61

This table show that when the number of units increases, the fuel cost, gas emission and average CPU decrease.

IV. CONCLUSION

In this paper, an approach based on the evolutionary algorithm has been presented and applied to environmental/economic power dispatch optimization problem. The problem has been formulated as a bi-objective optimization problem with competing fuel cost and environmental impact objectives. The proposed approach has a diversity-preserving mechanism to find Pareto-optimal solution. The optimal Pareto front is obtained from minimizing each objective function in each corridor and keeping the best individuals in dynamic achieves. Moreover, a fuzzy-based mechanism is employed to extract the best compromise solution over the trade-off curve. The results show that the proposed approach is efficient for solving bi-objective optimization where multiple Pareto-optimal solutions can be found in one simulation run. In addition, the non-dominated solutions in the obtained Pareto-optimal set are well distributed and have satisfactory diversity characteristics. Comparatively to other approach, the most important aspect of the proposed approach is the reduce time to find optimal Pareto front, fuel cost, gas emission, the consideration of unit commitment problem and the possibility to manage system which have n-generation units and best compromise.

REFERENCES

[1] Brodesky S. F, Hahn R. W. Assessing the influence of power pools on emission constrained economic dispatch. IEEE Trans Power Syst 1986;1(1).pp:57–62.

[2] Granelli G. P, Montagna M, Pasini G. L, Marannino P. Emission constrained dynamic dispatch. Electr Power Syst Res 1992;24.pp: 56–64.

[3] Chang C. S, Wong K. P, Fan B. Security-constrained multiobjective generation dispatch using bicriterion global optimization. IEE Proc—GenerTransmDistrib 1995;142(4):406–14.

[4] R Manoj Kumar. Bavisetti, T.KranthiKiran. Optimization Of Combined Economic and Emission Dispatch Problem – A Comparative Study for 30 Bus Systems. IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE) 2012 ;Vol 2 : PP 37-43

[5] M. A. Abido. Environmental/Economic Power Dispatch Using Multiobjective Evolutionary Algorithms. IEEE Transactions On Power Systems ; 2003 VOL. 18, NO. 4. Pp :1529-1537

[6] Alkhalil Firas. «Supervision, économie et impact sur l'environnement d'un système d'énergie électrique associé à une centrale photovoltaïque »thèse de Doctorat Paris tech. 2011

[7] Samani.h, Razmezani.M and Naseh.M.R. (2013). Unit Commitment and Methods for Solving; a Review .J. Basic. Appl. Sci. Res., 3(2s) 358-364

[8] Lubing Xie, Songling Wang & Zhiquan Wu. Study on Economic, Rapid and Environmental Power Dispatch. Modern applied sciences vol.3 N^{0}6. 2009. pp :38-44

[9] Jean Dipama. « Optimisation Multi-Objectif Des Systèmes Énergétiques ».thèse soutenue à l'université de Montréal. 2010

[10] Farid Benhamida, Rachid Belhachem. Dynamic Constrained Economic/Emission Dispatch Scheduling Using Neural Network .Power Engineering And Electrical Engineering.Volume: 11 N^{0}1 .2013.pp :1-9