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Optimization of Corridor Observation Method to Solve Environmental and Economic Dispatch Problem

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ABSTRACT:

This paper presents an optimization of corridor observation method (COM) which is an 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 optimization of this method consists to find best parameters (number of corridor, number of initial population and number of generation) which improve solution and reduce a computational time. The simulated results using power system with different numbers of generation units showed that the new parameters ameliorate the solution keep her stability and reduce considerably the CPU time (time is minimum divide by 4) comparatively at parameterization with originals parameters.

Keywords: *bi-objective, corridors observation, fuel cost, gas emission, new parameters, optimal Pareto front, optimization, original settings*

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, they are time-consuming and tend to observe 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, to conserve the non- dominated solutions during the search and relatively long time to find the solution.

In [8] we have proposed one method, based on the evolutionary method where the optimal Pareto front is obtained by the concept of corridor observation and the loses of non-dominated solution is reduce by the dynamism of archives during the different generations. The quality of solution and CPU time depend to the number of corridors, the initial population and the number of generations. In this paper, we propose some parameters which keep stable the solution and reduce considerably CPU time of COM. In the second part of this paper, we present materials and methods to solve the EED problem and in the third part, simulation and results are presented to enable us to find the new parameters and demonstrate their effectiveness by comparing it with the original settings.

II. MATERIALS AND METHODS [8]

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 ; $I_{i,t}$ the statut of different generators; ST_i the start-up cost .

- Minimization of gas emission

The atmospheric pollutants such as sulphur dioxides (SO_2) and nitrogen oxides (NO_X) caused by fossil-fuelled thermal units can be modelled 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 corridors observation method [8]

The different steps of the COM are presented in the following figure

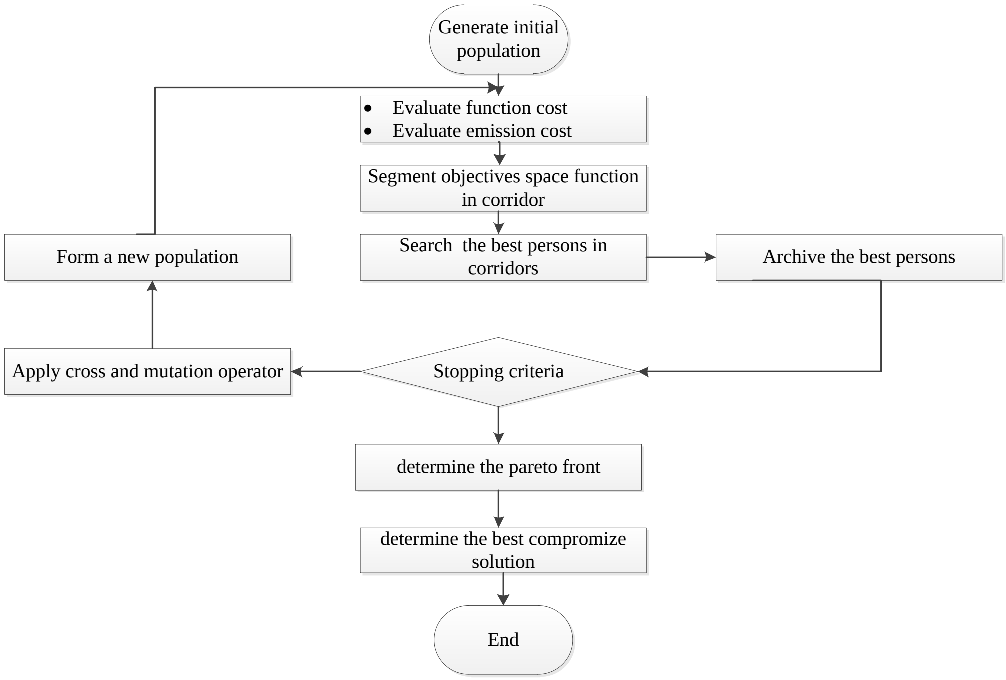

Figure 1: Different steps of the algorithms [8]

➢ **Step 1**

In the first step, we start with to the status of different units generation, where 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 observations following the different axes which are specify by each function.

- **Step 4**

In each corridor, we search the best individuals 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 stopping criteria define as [10]:

$$\xi = \ln(d) \qquad (9)$$

where

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

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

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

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

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

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

III. SIMULATION AND RESULTS

In order to find the new parameters of COM and solve the EED, a 3-units generation system is tested [11]. And extent at 6, 10 and 15 units generation. These parameters are applied in COM with the same software and computer used in [8]. The results are compared with the originals settings of COM. The data concerning the units generation are given in tables 1 and 2 [11].

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} (ton/h)	α_{Nox} (ton/h)	β_{so2} (ton/MWh)	β_{Nox} (ton/MWh)	δ_{so2} (ton/MW^{2}h)	δ_{Nox} (ton/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. Study of objectives according to the number of generation

The study of convergence with the same parameters of [8] i.e., 50 corridors, 300 number of initial population is presented in figure 2

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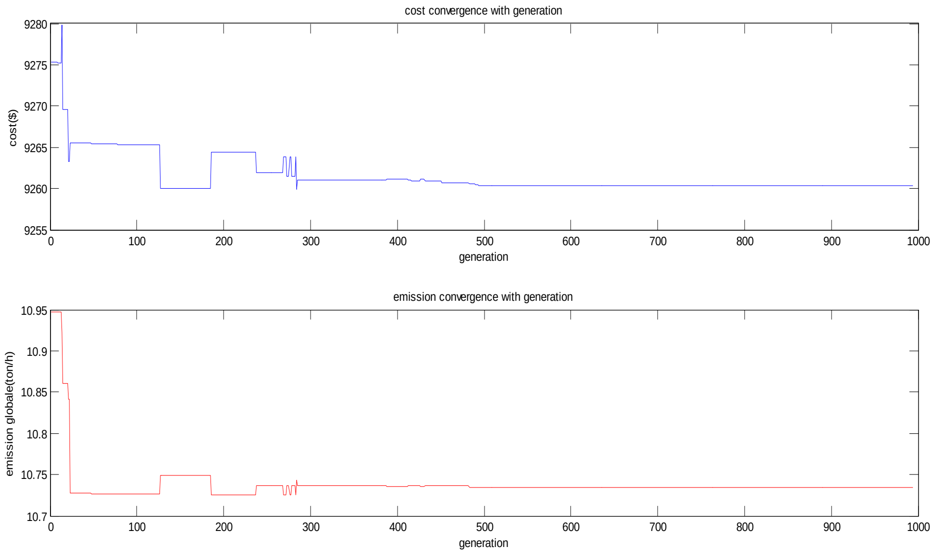

Figure 2: Convergence of fuel cost ($) and gas emissions (ton/h) objective functions (1000MW).

These curves convergence show that since the 500 generations fuel cost and gas emission is uniform so, if we choose the number of generations at the value greater or equal than 500 generations the solution will be the same. So we can take 500 like the new number of generations.

3.2. Study of objectives according to the number of corridors

The representation of objectives, according to the number of corridor, with initial population number and number of generations set respectively at 300 and 1000 is shown in figure 3.

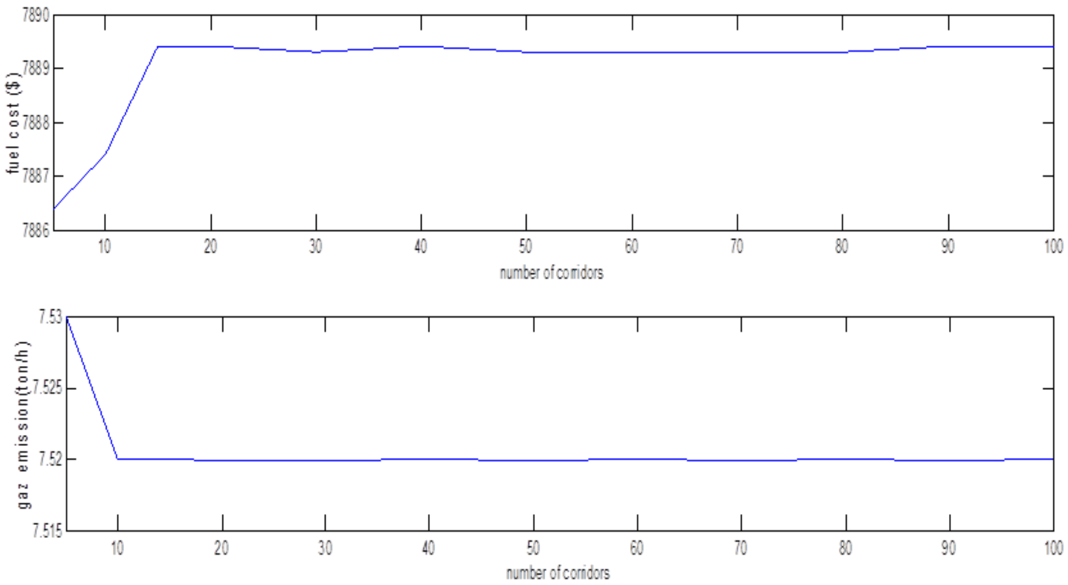

Figure 3: Evolution of fuel cost ($) and gas emissions (ton/h) according to the number of corridors (850 MW).
These curves shows that from 20 corridors fuel cost and gas emission are almost uniform. The Pareto front at this value of number of corridors is represented in figure 4.

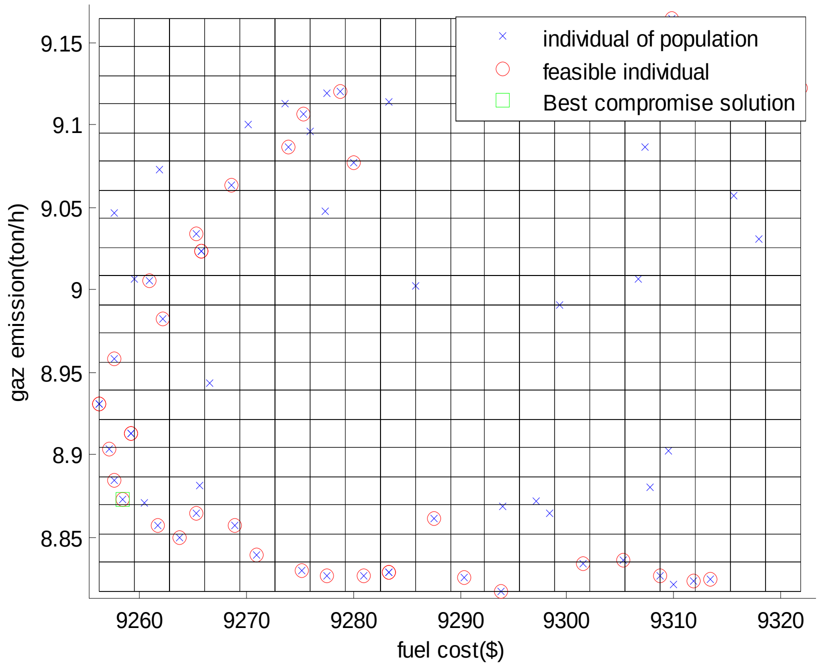

Figure 4: Pareto front with the new parameters.
Comparing with the Pareto front obtained with the original parameters [8] in figure 5

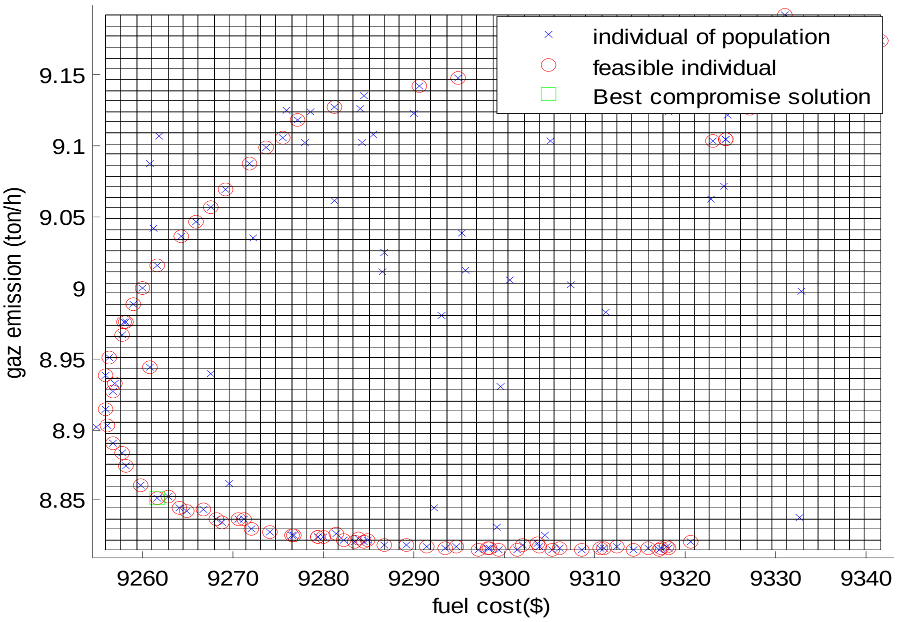

Figure 5: Pareto front with the original parameters.

We can conclude that the increase of corridors number improves the Pareto front but from 20 corridors, the optimal solution is almost uniform. So we can consider 20 like new number of corridor.

3.3. Study of objectives according to the number of initial population

The representation of objectives, according to initial population, with number of corridor and number of generations set respectively at 50 and 1000 is shown in figure

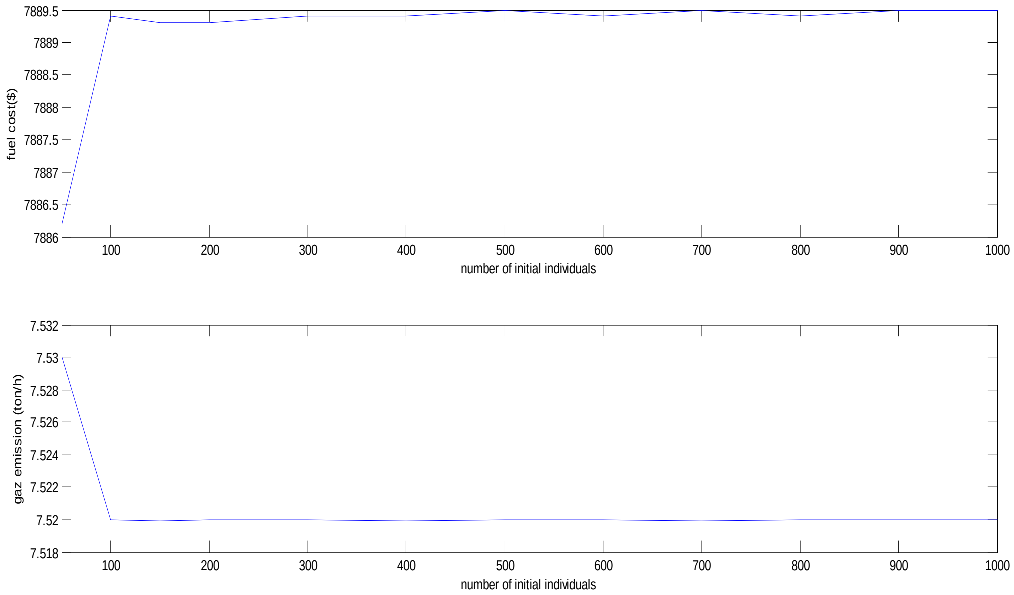

Figure 6: Evolution of fuel cost ($) and gas emissions (ton/h) according to the number of initial individuals (850MW)

These representations show that from an initial population of 200, fuel cost and gas emission are almost uniform. So we can set this parameter at 200.

3.4. Comparative study between the original parameters and new

To present the effectiveness of the new parameters in COM to unit commitment and EED, we applied it to a production plan of 3-units during 5 hours and made the comparison study with the original setting.

Table 3. Unit commitment and EED during 5 hours with the two groups of parameters

Hours (H)	Demands (MW)	P1 (MW)	P2 (MW)	P3 (MW)	Fuel cost X10^3($)	Emission gaz (ton/h)	Average CPU time (s)
With original parameters							
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	**23.29**
4	700	114.5484	0	585.351	6.4169	7.2059	
5	750	150.228	0	599.67	6.8777	7.7323	
With new parameters							
1	550	0	0	549.9	5.0417	5.6383	
2	600	0	0	599.9	5.4957	6.1468	
3	650	100.5037	0	549.39	5.9647	6.6967	**5.1**
4	700	106.2763	0	593.6432	6.4179	7.2054	
5	750	152.6171	0	597.32	6.8787	7.7343	

The findings of this table are as follows: in terms of unit commitment, the results are identical; sensibly the same in terms of EED but the CPU average times is considerably reduced. This study have extended with 6, 10, and 15 unit in table 4 findings was the same but the convergence speed according to the number of units is reduce with news parameters

Table 4. Comparative study with 3, 6, 10 and 15 units generation

Number of units	3	6	10	15
With original parameters				
Fuel cost x 10^3($)	9.2606	9.1911	9.176	9.177
Gas emission(ton/h)	10.7347	10.2771	10.3679	10.3683
Average times (s)	23.29	31.92	49.40	104.61
With new parameters				
Fuel cost x10^3($)	9.2583	9.1922	9.1844	9.1806
Gas emission (ton/h)	10.7617	10.1988	10.2854	10.3898
Average time (s)	5.14	5.74	7.03	34.30

IV. CONCLUSION

In this paper, news parameters are proposed to optimize COM. COM have been proposed in [8] to solve environmental/economic power dispatch optimization problem and unit commitment. The study of objectives according to the number of generation, of corridors and initial population have allowed us to propose new parameters that are 20 corridors, 200 individuals for initial population and 500 generations. The parameterization of COM with these settings conserves the quality of solution in terms of unit commitment and EED. The principal advantages of this parameterization are the reduction of CPU time (the time is minimum divided by 4) and the convergence speed according to the number of generation units comparatively at the parameterization with originals settings (50 corridors, 200 individuals and 1000 generation).

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