Economic and emission dispatch problems using a new hybrid algorithm

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***Abstract*— Environmental legislation, with its increasing pressure on the energy sector to control greenhouse gases, is a driving force to reduce CO_2 emissions, forced the power system operators to consider the emission problem as a consequential matter beside the economic problems, so the economic power dispatch problem has become a multi-objective optimization problem. This paper sets up an new hybrid algorithm combined in two algorithm, the harmony search algorithm and ant colony optimization (HSA-ACO), to solve the optimization with combined economic emission dispatch. This problem has been formulated as a multi-objective problem by considering both economy and emission simultaneously. The feasibility of the proposed approach was tested on 3-unit and 6-unit systems. The simulation results show that the proposed algorithm gives comparatively better operational fuel cost and emission in less computational time compared to other optimization techniques.**

Keywords—Economic Power Dispatch (EPD); Harmony Search Algorithm (HSA); Ant Colony Optimization (ACO.)

I. INTRODUCTION

The success of any stochastic search method heavily depends on striking an optimal balance between exploration and exploitation. These two issues are conflicting but very crucial for all the metaheuristic algorithms. Exploitation is to effectively use the good solutions found in the past search whereas exploration is expanding the search to the unexplored areas of the search space for promising solutions. The reinforcement of the pheromone trail by the artificial ants exploits the good solution found in the past. However, excessive reinforcement may lead to premature convergence. Many metaheuristic or optimization algorithms need some parameters to be set in order to obtain good solutions. Usually, those values are 'calculated' in an empirical (or heuristical) way. But this method is time consuming and it is not falling on the good values of the parameters.

Our work contributes to this problem by applying another metaheuristic method. The Harmony search algorithm (HSA) to find suitable values of parameters to validate our work we use to solve the problem of multi-objective optimization; the problem consists in combining the economic control system and the gas emission with the production of electrical energy.

The problem which has received much attention. It is of current interest of many utilities and it has been marked as one of the most operational needs. In traditional economic dispatch, the operating cost is reduced by the suitable attribution of the quantity of power to be produced by different generating units. However the optimal production cost can not be the best in terms of the environmental criteria. Recently many countries throughout the world have concentrated on the reduction of the quantity of pollutants from fossil fuel to the production of electrical energy of each unit. The gaseous pollutants emitted by the power stations cause harmful effects with the human beings and the environment like the sulphur dioxide (SO_2), nitrogen oxide (NO_x) and the carbon dioxide (CO_2), etc. Thus, the optimization of production cost should not be the only objective but the reduction of emission must also be taken into account. Considering the difference in homogeneity of the two equations, the equation of the cost of fuel given in $/hr, and the equation of emission of gases to the production of electrical energy given in Kg/hr.

This method was tested on 3-unit and 6-unit systems. The algorithm was developed MATLAB environment programming.

The proposed approach results have been compared to those that reported in the literature recently. The results are promising and show the effectiveness and robustness of the proposed approach.

II. ECONOMIC POWER DISPATCH FORMULATION

A. Problem formulation

1) Minimization of fuel cost

The goal of conventional EPD problem is to solve an optimal allocation of generating powers in a power system [1].

The power balance constraint and the generating power constraints for all units should be satisfied. In other words [2], the EPD problem is to find the optimal combination of power generations which minimize the total fuel cost while satisfying the power balance equality constraint and several inequality constraints on the system [3].

The total fuel cost function is formulated as follows [4]:

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

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

Where $f(P_G)$,is the total production cost ($/h).

$f_i(P_{Gi})$ is the fuel cost function of unit i in $/h;

P_{Gi} is the real power output of unit i in MW; a_i, b_i, c_i the cost coefficients of the i th generator.

B. Minimization of pollutants emission

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) [5]. These emissions can be modeled through functions that associate emissions with power production for each unit. One approach to represent SO_2 and NO_x emissions is to use a combination of polynomial and exponential terms [6]:

$$EC(Pg) = \sum \left(\alpha_i P_{gi}^2 + \beta_i P_{gi} + \gamma_i\right) + \varepsilon_i \exp\left(\lambda_i P_{gi}\right)$$

$$P_L = 0 \quad (3)$$

where

α_i , β_i, γ_i, ε_i and λ_i are coefficients of the ith generator emission characteristics..

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

Minimise F=FC+h*EC

Subjected to the power flow constraints of equations. The price penalty factor h blends the emission with fuel cost and F is the total operating cost in $/h.The price penalty factor hi is the ratio between the maximum fuel cost and maximum emssion of corresponding generator [7].

$$h_i = \frac{FC(P_{gi}^{\max})}{EC(P_{gi}^{\max})}$$

The following steps are used to find the price penalty factor for a particular load demand

1. Find the ratio between maximum fuel cost and maximum emission of each generator.

2. Arrange the values of price penalty factor in ascending order.

3. Add the maximum capacity of each unit $P_{gi}^{\max}$ one at a time, starting from the Smallest hi unit until $\sum P_{gi}^{\max} \geq P_d$

4. At this stage, hi associated with the last unit in the process is the price penalty factor h for the given load.

The above procedure gives the approximate value of price penalty factor computation for the corresponding load demand. Hence a modified price penalty factor (hm) is introduced in this work to give the exact value for the particular load demand. The first two steps of h computation remain the same for the calculation of modified price penalty factor. Then it is calculated by interpolating the values of hi corresponding to their load demand values.

C. Problem constraints

1) Active Power Balance equation

For power balance an equality constraint should be satisfied. The generated power should be the same as total load demand added to the total line losses. It is represented as follows:

$$\sum_{i=1}^{\mathrm{NG}} P_{Gi} = \sum_{j=1}^{\mathrm{ND}} P_{Dj} + P_L \quad (4)$$

$\sum_{j=1}^{\mathrm{ND}} P_{Dj}$ is the total system demand;

$\sum_{i=1}^{\mathrm{NG}} P_{Gi}$ is the total system production;

P_L is the total transmission loss of the system in MW;

NG is the number of generator units in the system;

ND is number of loads.

2) Active Power Generation limits

Generation power of each generator should be laid between maximum and minimum limits. There are following inequality constraints for each generator

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

$P_{Gi}^{\min}, P_{Gi}^{\max}$ are the minimum and maximum generation limits of the real power of unit i.

III. Harmony Search Algorithm (HSA)

Harmony search algorithm is a novel meta-heuristic algorithm, which has been conceptualized using the musical process of searching for a perfect state of harmony. This meta-heuristic is based on the analogy with music improvisation process where music players improvise the pitches of their instruments to obtain a better harmony. In the optimization context, each musician is replaced with a decision variable, and the possible notes in the musical instruments correspond to the possible values for the decision variables.

The harmony in music is analogous to the optimization solution vector, and the musician's improvisations are analogous to local and global search schemes in optimization techniques.

Musical performances seek to find pleasing harmony (a perfect state) as determined by an aesthetic standard, just as the optimization process seeks to find a global solution (a perfect state) as determined by an objective function [8].

The parameters of HS method are: the harmony memory size (HMS), the harmony memory considering rate (HMCR), the pitch adjusting rate (PAR), and the number of improvisations (NI). The harmony memory is a memory location where a set of solution vectors for decision variables is stored. The parameters HMCR and PAR are used to improve the solution vector and to increase the diversity of the search process. In HS, a new harmony (i.e., a new solution vector) is generated using three rules: 1) memory consideration, 2) pitch adjustment, and 3) random selection. It is convenient to note that the creation of a new harmony is called "improvisation". If the new solution vector (i.e., new harmony) is better than the worst one stored in HM, this new solution updates the HM. This iterative process is repeated until the given termination criterion is satisfied. Usually, the iterative steps are performed until satisfying the following criterions: either the maximum number of successive improvisations without improvement in the best function value, or until the maximum number of improvisations is satisfied [9].

A. *Initialize the problem and algorithm parameters*

The optimization problem is defined as follows:

Minimize *f(x)* subject to $x_i \in X_i$, *i=1,……., N.* where *f(x)* is the objective function, *x* is the set of each decision variable (x_i); X_i is the set of the possible range of values for each design variable, that is $X_{iL} < X_i < X_{iU}$.

Where X_{iL} and X_{iU} are the lower and upper bounds for each decision variables.

The HSA parameters are also specified in this step. They are the harmony memory size (HMS) [10], or the number of solution vectors in the harmony memory; harmony memory considering rate (HMCR); bandwidth (BW); pitch adjusting rate (PAR); number of improvisations (NI) or stopping criterion and number of decision variables (N).

B. *Initialize the harmony memory (HM)*

The harmony memory is a memory location where all the solution vectors (sets of decision variables) are stored. HM matrix is filled with as many randomly generated solution vectors as the HMS.

$$\text{HM}=\left[\begin{array}{cccc|c} x_1^1 & x_2^1 & \cdots & x_N^1 & f\left(x^1\right) \\ x_1^2 & x_2^2 & & x_N^2 & f\left(x^2\right) \\ \vdots & \vdots & \vdots & \vdots & \\ x_1^{HMS} & x_2^{HMS} & & x_N^{HMS} & f\left(x^{HMS}\right) \end{array}\right] \qquad (6)$$

C. *Improvise a new harmony*

A new harmony vector, $x' = (x'_1, x'_2, ..., x'_N)$, is generated based on the three rules: (1) memory consideration, (2) pitch adjustment and (3) random selection.

Generating a new harmony is called (improvisation).

The value of the first decision variable x'_1 for the new vector can be chosen from any value in the specified HM range $(x'_1 - x_1^{HMS})$.

Values of the other design variables $(x'_2, ..., x'_N)$ are chosen in the same manner.

HMCR, which varies between 0 and 1, is the rate of choosing one value from the historical values stored in the HM, while (1- HMCR) is the rate of randomly selecting one value from the possible range of values.

$$x'_i \leftarrow \begin{cases} x'_i \in \left\{x_i^1, x_i^2, ..., x_i^{HMS}\right\} & \textit{with probability HMCR} \\ x'_i \in \left(X_i\right) & \textit{with probability (1 - HMCR)} \end{cases} \qquad (7)$$

For instance, a HMCR of 0.95 indicates that the HSA will choose the decision variable value from historically [16] stored values in the HM with the 95% probability or from the entire possible range with the 100-95% probability. Every component of the New Harmony vector,

$x' = (x'_1, x'_2, ..., x'_N)$, is examined to determine whether it should be pitch-adjusted. This operation uses the PAR parameter, which is the rate of pitch adjustment as follows:

$$\begin{array}{l} \textit{Pitch adjusting} \\ \textit{decision for } x'i \end{array} \leftarrow \begin{cases} \textit{Yes} & \textit{with probability PAR} \\ \textit{No} & \textit{with probability (1 - PAR)} \end{cases} \qquad (8)$$

The value of (1- PAR) sets the rate of doing nothing. If the pitch adjustment decision for x' is Yes, x' is replaced as follows:

$$x'_i \leftarrow x'_i \pm rand * BW \qquad (9)$$

Where BW is an arbitrary distance bandwidth for the continuous design variable and rand is a random number between 0 and 1. In step 3, HM consideration, pitch adjustment or random selection is applied to each variable of the New Harmony vector in turn.

D. *Update harmony memory*

If the new harmony vector, $x' = (x'_1, x'_2, ..., x'_N)$, is better than the worst harmony in the HM, from the point of view of

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objective function value, the new harmony [11] is included in the HM and the existing worst harmony is excluded from HM.

E. Check the stopping criterion

If the stopping criterion (i.e.) maximum number of improvisations is satisfied, computation is terminated. Otherwise, Step 3 and 4 are repeated.

IV. Ant Colony Optimization

Colony Optimization is another powerful technique to solve hard combinatorial optimization problems. In ACO algorithms a finite number of artificial ants work together to search for the best solutions to the optimization problem under consideration. Each ant builds a solution and exchanges its information with other ants indirectly [12]. Although each ant can build a solution, high quality solutions are only found with this cooperation and information exchange [13].

In ACO algorithms a structural neighbourhood is defined for the given problem. Each ant builds a solution by moving in a sequence trough out the neighbourhood architecture. While building a solution each ant uses two different information sources.

The first source is private information which is the local memory of an ant and the second source is the publicly available pheromone trail together with problem specific heuristic information [14].

To build a feasible solution ants keep a tabulated list to keep the previously visited nodes. Publicly available pheromone trail provides knowledge about the decisions of ants from the beginning of the search process [15]. An ant-decision table defined with the functional combination of this pheromone trail and problem specific heuristic values is used to direct the search. Pheromone evaporation strategies are used to avoid stagnation due to large accumulations. Different ACO approaches like Ant System, Ant Colony System and Max Min Ant System are available in the literature [16]. The general structure for the ACO algorithms is as follows:

1. Initialize:

Set t=0

Set NC=0

For every edge (i,j) set an initial value τij(t)=c for trail

intensity and Δ τij=0

Place the m ants on the n nodes

2. Set s=1

For k=1 to m do

Place the starting town of the k-th ant in tabuk(s)

3. Repeat until tabu list is full

Set s=s+1

For k=1 to m do

Choose the town j to move to, with probability $P_{ij}^{k}(t)$ given

by equation (4)

Move the k-th ant to the towa j

Insert town j in tabuk(s)

4. For k=1 to m do

Move the k-th ant from tabuk(n) to tabuk(1)

Compute the length Lk of the tour described by the k-th ant

Update the shortest tour found

For every edge (i,j)

For k=1 to m do

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{Q_0}{L_k} if\,(i,j) \in tour \quad described \quad by \quad tabu_k \\ 0 \quad otherwise \end{cases}$$

$$\Delta\tau_{ij} = \Delta\tau_{ij} + \Delta\tau_{ij}^{k};$$

5. For every edge (j,j) compute $\tau_{ij}(t+n)$ according to equation $\tau_{ij}(t+n) = \rho\tau_{ij}(t) + \Delta\tau_{ij}$

Set t=t+n

Set NC=NC+1

For every edge (i,j) set $\Delta\tau_{ij}^{k} = 0$

6. If (NC<NCMAX) and (not stagnation bahavior)

then empty all tabu lists

Goto step 2

Elese

Print shortest tour

Stop

Where:

t: is the time counter

NC: is the cycles counter

S: is the tabu list index

$$m = \sum_{i=1}^{n} b_i(t) \tag{10}$$

m: is the total number of ants

$$P_{ij}^{k}(t)=\begin{cases}\dfrac{[\tau_{ij}(t)]^{\alpha}\cdot[\eta_{ij}]^{\beta}}{\sum\limits_{k\in allowed_k}[\tau_{ij}(t)]^{\alpha}\cdot[\eta_{ij}]^{\beta}} & if \quad j \in allowed_k\\ 0 & othervise\end{cases} \tag{11}$$

$P_{ij}^{k}(t)$: is the transition probability from town i to town j for the k-th ant as

N: is the set of towns

where allowed k = {N - tabuk}

$$\eta_{ij}=\frac{1}{d_{ij}} \tag{12}$$

$$\tau_{ij}(t+n)=\rho\tau_{ij}(t)+\Delta\tau_{ij} \tag{13}$$

ρ is a coefficient such that (1 - ρ) represents the evaporation of trail between time t and t+n,

η_{ij} : is the visibility

α and β are parameters that control the relative importance of trail versus visibility.

$$\Delta\tau_{ij}=\sum_{k=1}^{m}\Delta\tau_{ij}^{k} \tag{14}$$

$\Delta\tau_{ij}^{k}$: is the quantity per unit of length of trail substance (pheromone in real ants) laid on edge (i,j) by the k-th ant between time t and t+n; it is given by

Q_0 : is a constant and Lk is the tour length of the k-th ant.

V. APPROACH HSA-ACO

The reactive framework proposed in this paper focuses on α and β which have a great influence on the solution process.

The weight of the pheromone factor α, is a key parameter for balancing intensification and diversification.

Indeed, the greater α, the stronger the search is intensified around solutions containing components with

high pheromone trails, i.e., components that have been previously used to build good solutions.

The weight of the heuristic factor β, determines the greediness of the search and its best setting also depends on the instance to be solved. Indeed, the relevancy of the heuristic factor usually varies from an instance to another. More, for a given instance, the relevancy of the heuristic factor may vary during the solution construction process.

Adaptation of parameters α and β was performed by the HSA algorithm.

The proposed procedure steps are shown in Fig. 1.

The ACO parameter q0=0.8; $1 \le \beta \le 8$; $1 \le \alpha \le 8$, ρ= 0.5; Number of Ants (m) =57.

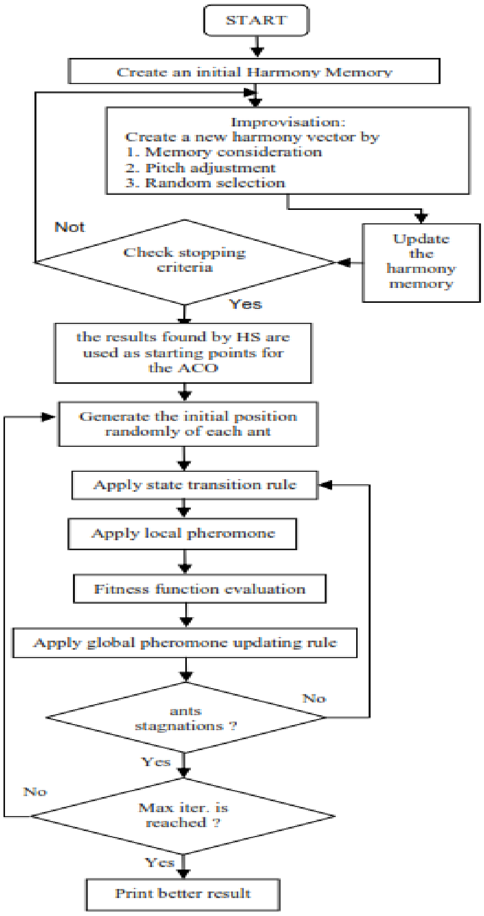

Fig. 1. Flow chart for EPD using HSA-ACO.

VI. SIMULATION RESULTS

To assess the efficiency of the approach HSA-ACO, the following two case studies are carried out. The program was developed using MATLAB and run on a 3.0 GHz, Pentium-IV machine with 256 MB RAM.

A. Test system 1

The 3 generators test system [17] whose data are given below. The system demand is 850 MW; is considered as test system 1, the fuel and the emission coefficients including the limits of generation for the generators are presented in tables I, II and III.

The results obtained by the proposed algorithm are compared to those reported in the literature like Tabu search (Roa-Sepulveda et al., 1996) [18], NSGA-II (AhKing & Rughooputh, 2003) [19], DE/BBO [20]. From the comparison, it is noticed that the proposed approach (HSA-ACO) gives reduction in fuel cost and the SO_2 emission and NO_x emission (Table IV). The convergence profiles of the best solution for the fuel cost and the SO_2 emission and NO_x emission are shown in Fig. 3, 4 and 5, respectively. It is noticed also from these figures that the convergence of the proposed approach (HSA-ACO) is promising , we got the results after only 30 iterations.

TABLE I. FUEL COST COEFFICIENTS (3-UNIT SYSTEM)

Bus No	Power limit (MW)		Cost Coefficients		
	P_{Gi}^{min}	P_{Gi}^{max}	a_i	b_i	c_i
1	150.0	600	0.001562	7.92	561.0
2	100	400	0.00194	7.85	310.0
3	50	200	0.00482	7.97	78.0

TABLE II. SO_2 EMISSION COEFFICIENTS (3-UNIT SYSTEM)

Unit i	α_i	β_i	γ_i
1	1.6103e-6	0.00816466	0.5783298
2	2.1999e-6	0.00891174	0.3515338
3	5.4658e-6	0.00903782	0.0884504

TABLE III. NO_X EMISSION COEFFICIENTS (3-UNIT SYSTEM)

	α_i	β_i	γ_i
1	1.4721848e-7	-9.4868099e-5	0.04373254
2	3.0207577e-7	-9.7252878e-5	0.055821713
3	1.9338531e-6	-3.5373734e-4	0.027731524

TABLE IV. COMPARISON OF TEST RESULTS OF 3-UNIT SYSTEM USING DIFFERENT METHODS FOR BI-OBJECTIVE.

Variable	DE/BBO [20]	NSGA-II [19]	Tabu [18]	Emission minimum HSA-ACO
PG1	435.1978	436.366	435.69	411.951833
PG2	299.9696	298.187	298.828	298.595129
PG5	130.6604	131.228	131.28	153.490052
cost ($/hr)	8344.58319	8344.651	8344.598	8342.952303
Emission SO_2(ton/h)	9.02194	9.02541	9.02146	8.983050
Emission NO_x (ton/h)	0.098686	0.098922	0.09863	0.088011
P_L(MW)	15.8289	15.781	15.798	14.0370
T (s)	/	/	/	0.62500

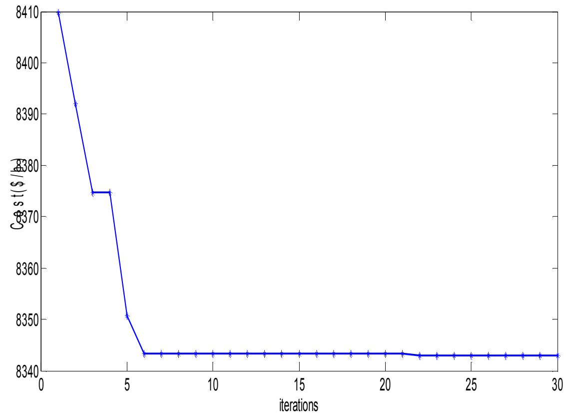

Fig. 2. Convergence characteristic for fuel cost minimization (3-unit system, demand 850 MW).

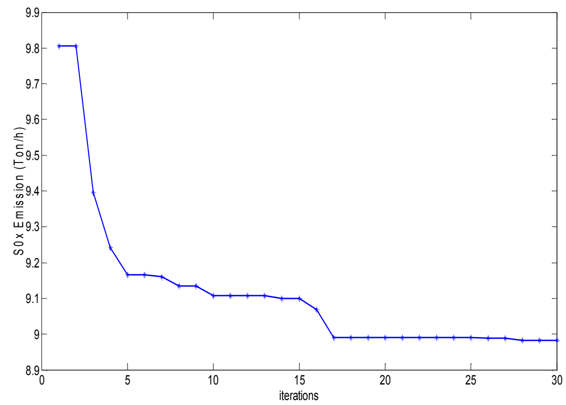

Fig. 3. Convergence characteristic for SO_2 emission minimization (3-unit system, demand 850 MW).

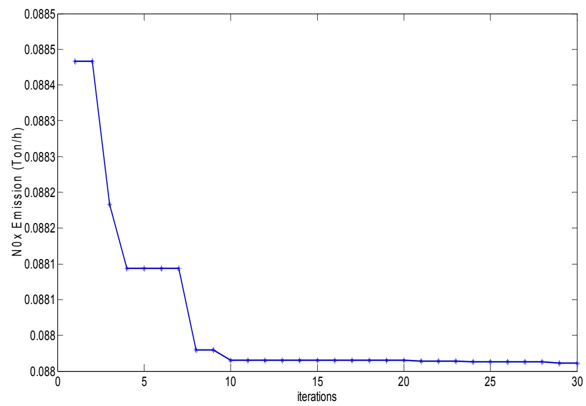

Fig. 4. Convergence characteristic for NO_x emission minimization (3-unit system, demand 850 MW).

B. Test system 2

A 6 generator test system [21] whose data are given below.

The system demand is 1200 MW; is considered as test system 2, the fuel and the emission coefficients including the limits of generation for the generators are presented in tables V and VI [21].The results obtained by the approach (HSA-ACO) are compared to those reported in the literature like QOTLBO, TLBO and DE [22]. From the comparison, it is noticed that the proposed approach (HSA-ACO) gives reduction in fuel cost and emission (Table VII).

The convergence profiles of the best solution for the fuel cost and the pollution emission are shown in Fig. 6 and 7, respectively. It is noticed also from these figures that the convergence of the proposed approach (HSA-ACO) is better; we got the results after only 30 iterations. These results clearly show the effectiveness and performance of the HSA-ACO over other methods.

TABLE V. POWER GENERATION LIMITS, COST CO-EFfiCIENT DATA OF GENERATING UNITS OF 6-UNIT SYSTEM.

Bus No	Real Power Output limit (MW)		Cost Coefficients $f_i(P_{Gi}) = a_i P_{Gi}^2 + b_i P_{Gi} + c_i$		
	P_{Gi}^{min}	P_{Gi}^{max}	a_i	b_i	c_i
1	10	125	0.15247	38.5390	756.7988
2	10	150	0.10587	46.1591	451.3251
3	35	210	0.03546	38.3055	1243.5311
4	35	225	0.02803	40.3965	1049.9977
5	125	325	0.01799	38.2704	1356.6592
6	130	325	0.02111	36.3278	1658.5696

TABLE VI. POWER GENERATION LIMITS, EMISSION CO-EFfiCIENT DATA OF GENERATING UNITS OF 6-UNIT SYSTEM.

Bus No	Cost Coefficients $EC(Pg) = \sum_{j=1}^{ND} (\alpha_i P_{gi}^2 + \beta_i P_{gi} + \gamma_i)$		
	α_i	β_i	γ_i
1	0.00419	0.32767	13.8593
2	0.00419	0.32767	13.8593
3	0.00683	-0.54551	40.2669
4	0.00683	-0.54551	40.2669
5	0.00461	-0.51116	42.8955
6	0.00461	-0.51116	42.8955

TABLE VII. COMPARISON OF TEST RESULTS OF 6-UNIT SYSTEM USING DIFFERENT METHODS FOR BI-OBJECTIVE.

	QOTLBO [22]	TLBO [22]	DE [22]	Emission minimum HSA-ACO
P_{G1}	107.3101	107.8651	108.6284	123.151188
P_{G2}	121.4970	121.5676	115.9456	142.179593
P_{G5}	206.5010	206.1771	206.7969	187.070320
P_{G8}	206.5826	205.1879	210.0000	168.631233
P_{G11}	304.9838	306.5555	301.8884	319.977087
P_{G13}	304.6036	304.1423	308.4127	297.412602
cost ($/hr)	64912	64922	64843	64136.543135
Emission (Ib/h)	1281	1281	1286	1280.107267
P_L(MW)	51.4781	51.4955	51.700	38.4000
T (s)	1.91	2.18	3.09	0.20313

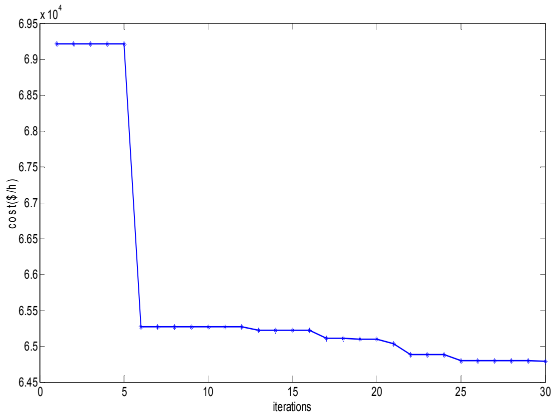

Fig. 5. Convergence of cost obtained for 6-unit test system.

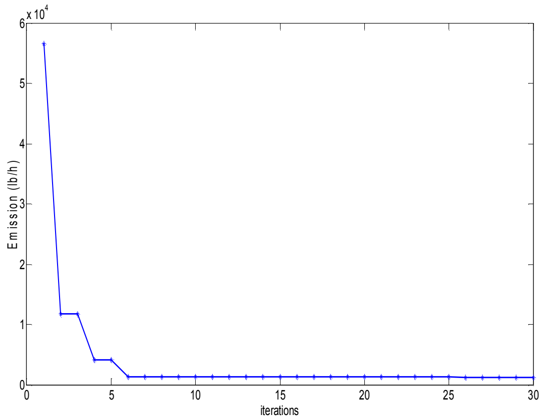

Fig. 6. Convergence of emission for 6-unit test system.

VII. CONCLUSION

In this article we have applied a new approach that involves a combination of two Meta heuristic methods based in

Harmony search Algorithm (HSA) and ant colony algorithm (ACO). Proposed approach was tested on 3-unit and 6-unit systems.

The obtained results were compared to those of other researchers. The results show clearly the robustness and efficiency of the proposed approach in term of precision and convergence time

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