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Solution of combined heat and power dispatch using artificial hummingbird optimization algorithm

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ABSTRACT

This article presents a new bio inspired optimization algorithm technique i.e.Artificial Hummingbird Algorithm (AHA) to solve combined heat and power dispatch (CHPD) problem with bounded feasible operating region. The AHA algorithm simulates the special flight skills and intelligent foraging strategies of hummingbirds in nature. AHA is validated in two different test systems containing different number of power, heat and combined unit. The results of the AHA algorithm are compared with other popular optimization techniques like Particle Swarm Optimization (PSO), Classical Particle swarm optimization (CPSO), Time varying acceleration coefficients particle swarm optimization (TVAC-PSO),Teaching learning based optimization (TLBO),Oppositional Teaching learning based optimization (OLTBO). The simulation results shows that, AHA provides better results than all other optimization techniques in-terms of cost and computational time.

Keywords: combined heat and power dispatch, Artificial Hummingbird Algorithm, cost minimization, Co-generation

1. Introduction:

As we know, in all the power plants the most common loss is the heat loss. The combined heat and power system uses the heat generated by the machines and increases the efficiency of the overall system. The normal efficiency of the CHP system ranges from 75-95%. Combined heat and power (CHP) plants use the waste heat from electricity production for heating purposes, normally for district or industrial heating. Therefore Cogeneration or combined heat and power (CHP) is well-organized, hygienic, and consistent approach to generating power and thermal energy from a single fuel source. This system has a higher efficiency as compared to other systems and it releases less green house gas in the atmosphere. This system uses the combined dependence of heat and power. With the increase in power demand we also have to increase the efficiencies of the power generation.

In 2015, Yang Li a *et al.* [1] To address the problem of combined heat and power economic emission dispatch (CHPEED), a two-stage approach is proposed by combining multi-objective optimization (MOO) with integrated decision making (IDM). First, a practical CHPEED model is built by taking into account power transmission losses and the valve-point loading effects. To solve this model, a two-stage methodology is thereafter proposed. The first stage of this approach relies on the use of a powerful multi-objective evolutionary algorithm, called θ-dominance based evolutionary algorithm (θ-DEA), to find multiple Pareto-optimal solutions of the model. Through fuzzy c-means (FCM) clustering, the second stage separates the obtained Pareto-optimal solutions into different clusters and thereupon identifies the best compromise solutions (BCSs) by assessing the relative projections of the solutions belonging to the same cluster using grey relation projection (GRP).

In 2012 [3]. A novel time varying acceleration coefficient particles swarm optimization (TVAC-PSO) algorithm [4] is implemented to solve combined heat and power economic dispatch (CHPED) problem. The CHPED problem is a challenging known convex and non linear optimization problem. Time varying acceleration coefficients PSO is implemented to obtain better solutions. The obtained results demonstrate the superiority of the proposed method in solving non-convex and constrained CHPED problem. Roy *et al.* applied teaching learning based optimization (TLBO) [5] to solve CHPD problem and bounded feasible operating region. B-colony optimisation algorithm [6] inspired by the foot foraging behaviour of honey bees is successfully applied by M. Basu to solve CHPD problem. The optimal utilisation of multiple combined heat and power (CHP) systems is a complex problem. Therefore, efficient methods are required to solve it. In this paper, [7] a recent optimisation technique, namely mesh adaptive direct search (MADS) is implemented to solve the combined heat and power economic dispatch (CHPED) problem with bounded feasible operating region. This MADS method is illustrated using three test cases. The LHS, PSI and DACE algorithms are employed on effective search strategies in MADS to solve each of the CHPED problem. The performance of the utilised MADS-LHS, MADS-PSO, MADS-DACE methods are compared to that of other techniques. The results clearly demonstrate that the MADS methods are practical and valid for CHPED applications. Whale optimization algorithm which is inspired from the prey predator concept of whales is applied to solve CHPD problem in [8]. The problem includes power loss and thermal production in transmission systems.

Basu M. Group search optimization for combined heat and power economic dispatch. Int J Electr Power Energy Syst 2016 [9].Although this algorithm belongs to the Meta-Heuristic this is different for its biological background. This method is inspired from the three flight skills and three foraging strategies of hummingbirds in nature. In this paper AHA algorithm is proposed for solving the problems of CHPED with considering the transmission loss. In this system we have taken 2 test cases consisting 7, 24 units. AHA already proves its superiority over other algorithms when applied to benchmark functions. These features of AHA motivate the authors to apply this algorithm to solve CHPD problem.

2. Problem formulation:

The objective of the CHPD is to find the optimal scheduling of power and heat generation with minimum fuel cost such that both heat and power demands and other constraints are met while the combined heat and power units are operated in a bounded heat versus power plane. The objective function may mathematically be expressed as follows:

$$\min C = \sum^{n_p} c_i(p_i) + \sum^{n_c} c_j(p_j, h_j) + \sum^{n_h} c_k(h_k)$$

(1)

$i=1$ $j=1$ $k=1$

where n_p, n_c and n_h are the number of conventional thermal units, cogeneration units and heat only units, respectively; C is the total cost; h_j and p_j are the heat and power output of the j^{th} unit.

$$c_i(p_i) = a_i(p_i)^2 + b_i p_i + c_i \tag{2}$$

$$c_i(p_i) = a_i(p_i)^2 + b_i p_i + c_i + |d_i \times \sin(e_i \times (p_i^{\min} - p_i))| \tag{3}$$

$$c_j(p_j, h_j) = a_j(p_j)^2 + b_j p_j + c_j + d_j(h_j)^2 + e_j h_j + f_j h_j p_j \tag{4}$$

$$c_k(h_k) = a_k(h_k)^2 + b_k h_k + c_k \tag{5}$$

- Power balance constraints

$$\sum_{i=1}^{n_p} p_i + \sum_{j=1}^{n_c} p_j = p_d + p_{loss} \tag{6}$$

Where p_d is electric power demand and p_{loss} is the transmission loss of the system and stated as follows:

$$p_{loss} = \sum_{i=1}^{n_p}\sum_{q=1}^{n_p} p_i B_{iq} p_q + \sum_{i=1}^{n_p}\sum_{j=1}^{n_c} p_i B_{ij} p_j + \sum_{j=1}^{n_c}\sum_{s=1}^{n_c} p_j B_{js} p_s \tag{7}$$

- Heat production and demand balance:

$$\sum_{j=1}^{n_c} h_j + \sum_{k=1}^{n_h} h_k = h_d \tag{8}$$

- Capacity limit of conventional unit:

$$p_i^{\min} \le p_i \le p_i^{\max} \qquad i = 1,2,\dots\dots\dots,n_p \tag{9}$$

- Capacity limits of CHP units:

$$p_j^{\min}(h_j) \le p_j \le p_j^{\max}(h_j)$$

$$h_j^{\min}(p_j) \le h_j \le h_j^{\max}(p_j) \qquad j = 1,2,\dots\dots\dots,n_c \tag{10}$$

3. Artificial humming bird algorithm:

Humming birds are regarded to be the smartest and brightest animals on the earth AHA Algorithm is inspired from the unique fight skills and brilliant foraging strategies of humming birds. There are basically two special skills of hummingbirds which builds the AHA Algorithm and these are:

- **Foraging skills:** hummingbirds have amazing memory for foraging. Their memory holding capacity is vast. In fact each hummingbird can remember distinct information about particular flowers in a given region. Including the location.

- **Flight skills:** Hummingbirds display such intricate flight skills that no other birds could follow. They have their flight skills, that are: (i) Axial flight, (ii) diagonal flight, (iii) omnidirectional flight. Axial flight enables the hummingbird to fly along any coordinate axis, the diagonal flight feature enables the hummingbird to shift from one corner of the rectangle to the opposite one and can be found out by any of the two coordinates.

Mathematical Model:

Initialisation

Let us take a number of m hummingbirds which are placed on m number of food sources and form an equation as follows:

$$x_i = lb + r.(ub - lb) \quad i = 1,.....n \tag{11}$$

So, the visit table of food sources is given as:

$$Vta_{i,j} = \begin{cases} 0 & if\ i \neq j \\ null & i = j \end{cases} \qquad i = 1,...n;\ j = 1,...n$$ When, x= y, $Vta_{i,j}$ =null

It indicates that at a specific food source a hummingbird is taking its food.

When, i ≠j, $Vta_{i,j}$= 0. It indicates that in the current iteration the xth hummingbird just visited the **y**th food source.

Guided foraging

Each hummingbird has a natural tendency to visit t6he food source which has the maximum nectar volume. It indicates high refilling rate of the target source and a long unvisited time by that hummingbird. In guided foraging, a hummingbird determines the food source which has the highest visit level, then it chooses the food source which has the highest nectar-refilling rate. There are three flight skills during foraging, which are:

a) axial flight b) diagonal flight c) omnidirectional flight

In the AHA algorithm, these flights are used and modelled with the introduction of switch vector which is used to control whether one or more directions in the d-dimension space are available. All birds use omnidirectional flight but only hummingbirds can master the axial and diagonal flights.

The axial flight pattern in a d-D space can be written in the form of an equation as follows:

$$D^{(i)} = \begin{cases} 1 & if\ i = randi([1,d]) \\ else & \\ 0 & \end{cases} \quad i = 1,...d \tag{12}$$

The diagonal flight pattern in a d-D space:

$$D^{(i)} = \begin{cases} 1 & if\ \ i = P(j), j \in [1,k], P = randperm(k), k \in \left[2, \left[r_1.(d-2)\right]+1\right] \\ else & \\ 0 & \end{cases} \quad i = 1,...d \tag{13}$$

The omnidirectional flight pattern in a d-D space:

$$D^{(i)} = 1 \quad i = 1,...d$$

Here, randx([1,d]) denotes a random integer from 1 to d , randperm (l) generates a random permutation of integers from 1 to l , r_1 denotes random number in (0, 1]. The diagonal flight in a d-D space is inside a hyperrectangle which is by any 2 to d-1 coordinate axes.

abilities which results in obtaining a candidate food source.

A mathematical equation is formed which simulates the guided foraging behaviour and a candidate food source is derived as follows:

Equation (14) enables each current food source to update its position in the neighbourhood of the target food source and models the guided foraging of of hummingbird by different flight patterns. The updated position of the *xth* food source is :

$$v_i(t+1) = x_{i,tar}(t) + a.D.(x_i(t) - x_{i,tar}(t)) \tag{14}$$

$$b \sim N(0,1) \tag{15}$$

After performing guided foraging, if there is not a better nectar refilling rate the hummingbird will not change its food source but if there is a better nectar refilling rate than the current food source will be replaced by a new one and then this hummingbird will stay at its new food source.

Territorial Foraging:

A hummingbird after visiting its target food source where the flower nectar has been eaten searches for a new food source instead of visiting the other already existing food sources. So a hummingbird moves to its neighbouring region within its own territory. A new food source as a candidate solution may be found in the neighbouring region which may be better than the current food source. A mathematical equation is formed which simulates the local search of hummingbirds in the territorial foraging strategy and a candidate food source is obtained :

$$x_i(t+1) = \begin{cases} x_i(t) & f(x_i(t)) \le f(v_i(t+1)) \\ v_i(t+1) & f(x_i(t)) > f(v_i(t+1)) \end{cases} \tag{17}$$

$$v_i(t+1) = x_i(t) + b.D.x_i(t) \tag{18}$$

Here, c = territorial factor subjected to the normal distribution M(0, 1) with mean=0 and standard deviation = 1.

Migration Foraging

A hummingbird migrates to a food source which is more distant from the current one for feeding when the region where it frequently visits has a tendency of lack of food. In the AHA algorithm, a migration coefficient is defined. When the number of iterations exceeds the predetermined value of the defined migration coefficient , the hummingbird which is at the food source that has the worst nectar-refilling will migrate to new food source produced in the entire search space. So the hummingbird will leave the old food source and stay at the new one for feeding.

A mathematical equation is formed for the migration foraging of the hummingbird:

$$x_{wor}(t+1) = lb + r.(ub - lb) \tag{19}$$

Here, x_{wor} = the food source that has the worst nectar refilling rate in the population.

1. Result and Discussion:

In order to verify the effectiveness of AHA , its has been tested on two test system. All the coding has been done in MATLAB 2013, on a personal computer having 2.53 GHz core i3 processor with 3 GB RAM. Results obtained by AHA Algorithm has been compared with PSO, CPSO, TLBO, and TVAC-PSO to show the superiority of AHA algorithm. The detailed results have been discussed below:

Test System 1:

This test system consists of total 7 units out of which four are power only units, one is heat unit and two cogeneration units. The feasible operating regions of the two cogeneration units are shown in Figs. 1 and 2. The system power demand and the heat demand are respectively 600 MW and 150 MWth. The full system data including operating limits of conventional power units' active power and heat only units' heat and cost coefficient data of different conventional power units, cogeneration units and heat only is taken from [5].

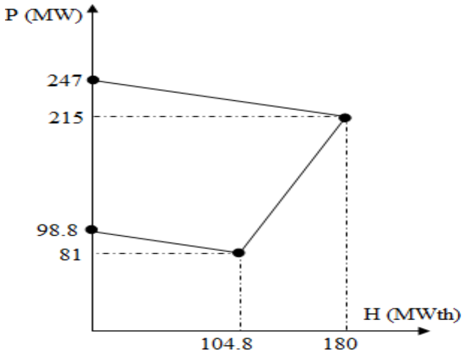

Fig. 1. Feasible region of CHP units of (5 of test case 1) (14 and 16 of test case 2)

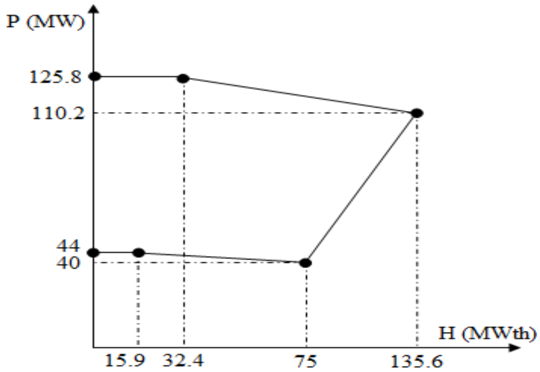

Fig. 2. Feasible region of CHP units of (6 test case 1) (15 and 17 of test case 2)

The simulation results of the proposed artificial hummingbird algorithm are shown in table 1. A result comparison among different methods have been listed in table 2. It is observed that after applying AHA, the total cost obtained is much lesser than the costs obtained by using the using PSO, EP, DE, RCGA, BCO and CPSO algorithm. The cost convergence characteristics is illustrated in fig. 3. AHA method obtained lowest cost of 10111.121 ($) as compared to PSO (10613), EP (10390), DE (10317), RCGA (10667), BCO (10317), CPSO (10325.3339). we also got the lowest CPU time 2.78 as compared to PSO (5.3844), EP (5.2750), DE (5.2563), RCGA (6.4723), BCO(5.1563), CPSO(3.29).

Table 1. Simulation results obtained by different techniques for Test case 1

Control variables	PSO	EP	DE	RCGA	BCO	CPSO	AHA
P1 (MW)	18.4626	61.361	44.2118	74.6838	43.9475	75.0000	52.6614
P2 (MW)	124.2602	95.1205	94.5383	97.9578	98.5888	112.3800	98.5407
P3 (MW)	112.7794	99.9427	112.6913	167.2308	112.932	30.0000	112.6765
P4 (MW)	209.8158	208.7319	209.7741	124.9079	209.7719	250.0000	209.8166
P5 (MW)	98.814	98.8000	98.8217	98.8008	98.8000	93.2701	93.8518

P6 (MW)	44.0107	44.0000	44.0000	44.0001	44.0000	40.1585	40.0007
H5 (MW)	57.9236	18.0173	12.5379	58.0965	12.0974	32.5655	29.1337
H6 (MW)	32.7603	77.5548	78.3481	32.4116	78.0236	72.6738	75.0006
H7 (MW)	59.3161	54.3739	59.1139	59.4919	59.879	44.7606	45.8655
Cost ($)	10613	10390	10317	10667	10317	10325.3339	10111.121

Table 2. Results comparison among different methods for Test case 1

Algorithms	Best fuel cost ($)	Average fuel cost ($)	Worst fuel cost ($)	Average CPU time
PSO	10613	NA	NA	5.3844
EP	10390	NA	NA	5.2750
DE	10317	NA	NA	5.2563
RCGA	10667	NA	NA	6.4723
BCO	10317	NA	NA	5.1563
CPSO	10325.3339	NA	NA	3.29
AHA	10111.1214	10111.8891	10126.4739	2.78

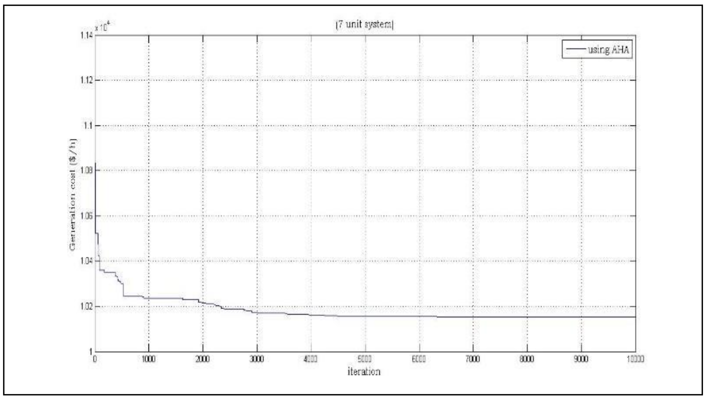

Fig. 3. cost convergence characteristics of AHA for test system 1.

Test System 2:

A little more complex system consisting 24 units out of which there are 13 power only units, 6 CHP units and 5 heat only units are considered in this case. The full system data along with cost coefficients and operating limits of power only and heat only units are taken from [5]. Total power demand of 2350 MW

and heat demand of 1250 MWth are used in this simulation study. The feasible operating regions of the 6 cogeneration units are shown in Figs. 1, 2,4 and 5.

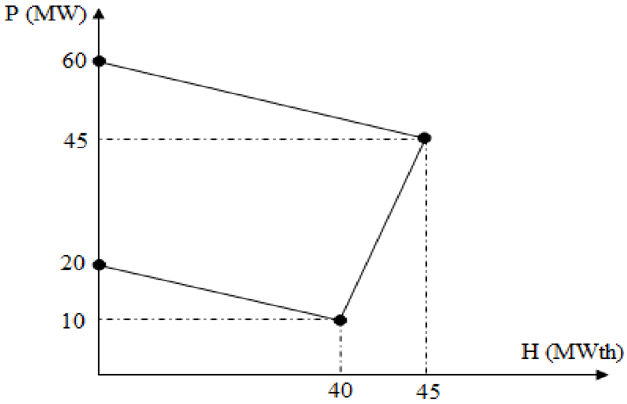

Fig. 4: Feasible region of CHP units (18 of test case 2)

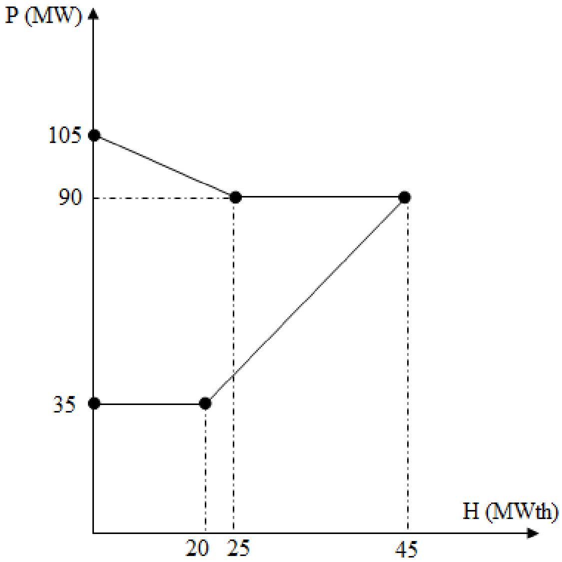

Fig. 5: Feasible region of CHP units (19 of test case 2)

The simulation results of the proposed artificial hummingbird algorithm are shown in the column 6 of table 3 and their results are compared with the results obtained using CPSO, TVAC-PSO, TLBO and OLTBO algorithm. From the table 4 it is observed that after applying AHA, the total cost obtained is much lesser than the costs obtained by using the using CPSO, TVAC-PSO, TLBO and OLTBO algorithm. The cost convergence characteristics is illustrated in fig. 6. By applying the AHA method we have got the lowest cost of 57568.8802 ($) as compared to CPSO (59736.2635), TVAC-PSO (58122.7460), TLBO (58006.9992), OLTBO (57856.2676). We also got the lowest CPU time 5.47 as compared to CPSO (8.00), TVAC-PSO (7.84), TLBO (5.67), OLTBO (5.82).

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Table 3. Simulation results obtained by different techniques for Test case 2

Control Variables	CPSO	TVAC-PSO	TLBO	OLTBO	AHA
P1 (MW)	680.0000	538.5587	628.3240	538.5656	359.0787
P2 (MW)	0.000	224.4608	227.3588	299.2123	298.2058
P3 (MW)	0.0000	224.4608	225.9347	299.1220	298.9835
P4 (MW)	180.0000	109.8666	110.3721	109.9920	159.7370
P5 (MW)	180.0000	109.8666	110.2461	109.9545	110.2384
P6 (MW)	180.0000	109.8666	160.1761	110.4042	159.9487
P7 (MW)	180.0000	109.8666	108.3552	109.8045	60.0000
P8 (MW)	180.0000	109.8666	110.5379	109.6862	110.3229
P9 (MW)	180.0000	109.8666	110.5672	109.8992	159.7378
P10 (MW)	50.5304	77.5210	75.7562	77.3992	40.0000
P11 (MW)	50.5304	77.5210	41.8698	77.8364	115.0482
P12 (MW)	55.0000	120.0000	92.4789	55.2225	92.5679
P13 (MW)	55.0000	120.0000	57.5140	55.0861	60.8684
P14 (MW)	117.4854	88.3514	82.5628	81.7524	81.0489
P15 (MW)	45.9281	40.5611	41.4891	41.7615	40.0607
P16 (MW)	117.4854	88.3514	84.7710	82.2730	81.0584
P17 (MW)	45.9281	40.5611	40.5874	40.5599	44.5037
P18 (MW)	10.0013	10.0245	10.0010	10.0002	7.7393
P19 (MW)	42.1109	40.4288	31.0978	31.4679	86.3296
H14 (MWth)	125.2754	108.9256	105.6717	105.2219	104.8274
H15 (MWth)	80.1174	75.4844	76.2843	76.5205	74.1024
H16 (MWth)	125.2754	108.9256	106.9125	105.5142	104.8328
H17 (MWth)	80.1174	75.4840	75.5061	75.4833	78.8878
H18 (MWth)	40.0005	40.0104	39.9986	39.9999	55.0000
H19 (MWth)	23.2322	22.4676	18.2205	18.3944	45.0000
H20 (MWth)	415.9815	458.7020	468.2278	468.9043	435.1458
H21 (MWth)	60.0000	60.0000	59.9867	59.9994	60.0000
H22 (MWth)	60.0000	60.0000	59.9814	59.9999	60.0000
H23 (MWth)	120.0000	120.0000	119.6074	119.9854	115.6592
H24 (MWth)	120.0000	120.0000	119.6030	119.9768	116.5443
Cost($)	59736.2635	58122.7460	58006.9992	57856.2676	57568.8802

Table 4. Results comparison among different methods for Test case 2

Algorithms	Best fuel cost ($)	Average fuel cost ($)	Worst fuel cost ($)	CPU time
CPSO	59736.2635	59853.478	60076.6903	8.00
TVAC-PSO	58122.7460	58198.3106	58359.5520	7.84
TLBO	58006.9992	58014.3685	58038.5273	5.67
OLTBO	57856.2676	57883.2105	57913.7731	5.82
AHA	57568.8802	57570.6320	57603.9211	5.47

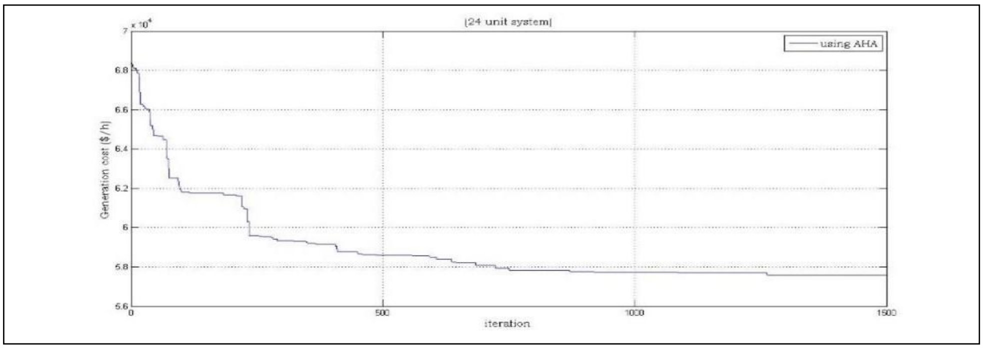

Fig.6. cost convergence characteristics of AHA
for test system 2.

2. Conclusion:

In this paper a novel optimization algorithm known as Artificial humming bird optimization is proposed to solve combined heat and power dispatch problem. The generation cost of CHPD unit has been minimized. Based on foraging skills and fight skill, this algorithm is works. To validate the performance of this algorithm, two different test cases have been considered. Each test system consists of different power, heat and combined unit. The results obtained by AHA algorithm has been compared with other established algorithms listed in the literature. It is observed from results that, AHA attained lowest cost and simulation time compared to other algorithms. So, in future it can be applied to solve other power system optimization problem.

Reference:

[1] Zidan A, Gabbar H A, Eldessouky A. Optimal planning of combined heat and power systems within microgrids. Energy 2015, 93: 235-244.

[2] Song, Y.H., Chou, C.S. and Stonham, T.J., "Combined heat and power economic dispatch by improved an colony search algorithm", Electric Power Systems Research, vol. 52,pp. 115-121, 1999.

[3] Basu, M., "Artificial immune system for combined heat and power dispatch", Int. J. of Electrical Power

and Energy Systems, vol. 43, pp. 1-5, 2012.

[4] Ivatloo, B. M., Moradi-Dalvand, M. and Rabiee A. , "Combined heat and power economic dispatch problem solution using particles warm optimization with time varying acceleration coefficients", Electric Power Systems Research, vol. 95, pp.9-18,2013.

[5] Provas Kumar Roy, Chandan Paul, A new optimization technique of Combined Heat and Power Dispatch using TLBO, Power System ,Vol, 10 (2014).

[6] Basu, M., "Bee colony optimization for combined heat and power economic dispatch", Expert Systems with Applications, vol. 38, pp. 13527-13531, 2011.

[7] Seyyed Soheil Sadat Hosseini, Ali Jafarnejad, Amir Hossein Behrooz, and Amir Hossein Gandomi. “Combined heat and power economic dispatch by mesh adaptive direct search algorithm”. Expert Syst. Appl. 38, 6556–6564, 2011.

[8] T.Kalapriyan, J Amudhavel, Whale Optimization Algorithm for Combined Heat and Economic Power Dispatch, Advances And Applications in Mathematical Sciences ,Vol 17, pp-.197-211,2017.

[9] Basu M. Group search optimization for combined heat and power economic dispatch. Int J Electr Power Energy Syst 2016, 78: 138-147