ARTIFICIAL BEE COLONY OPTIMIZATION FOR THE COMBINED HEAT AND POWER ECONOMIC DISPATCH PROBLEM

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ABSTRACT

This paper presents a new approach for solving the Combined Heat and Economic Dispatch (CHPED) problem using an artificial bee colony algorithm (ABC). Artificial Bee Colony algorithm (ABC) is inspired by the foraging behavior of honey bee swarm, is a biological inspired optimization. It shows more effective than the other optimization algorithms. The performance of the proposed algorithm ABC is validated by illustration with single area cogeneration test system. The results of the proposed algorithm are compared with those of Practical Swarm Optimization (PSO), ABC, Real -Coded Genetic Algorithm (RCGA), Bee Colony Optimization (BCO) and Evolutionary Programming techniques (EP). From numerical results, it is seen that the proposed algorithm is able to provide a better solution at a lesser computational effort.

Keywords: combined heat and power economic dispatch, artificial bee colony optimization, cogeneration.

1. INTRODUCTION

The conversion of primary fossil fuel into electricity is an inefficient process. Even the most modern combined cycle plants can only obtain efficiency between 50%-60% [1]. Most of the energy wasted in the conversion process is released in to the environmental as waste heat. The principle of combined heat and power, known as cogeneration, is to recover and make beneficial use of this heat and as a result the overall efficiency of the conversion process is increased to 90% [1]. The combined heat and power generation has higher energy efficiency and less green house gas emission as compared with other forms of energy supply. Recently, cogeneration units have been extensively used in industry. The heat production capacity of most cogeneration units depends on the power generation and vice versa. The mutual dependencies of heat and power generations introduce a complication in the integration of cogeneration units into the power system + economic dispatch. The objective of Economic Dispatch (ED) problem in a conventional power plant is to find the optimal point for the power production such that the demand matches the generation with production fuel cost. However, the objective of CHPED is to find the optimal point of power and heat generation with production 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.

A technique developed in [2] called as dual and quadratic programming used to solve the CHPED problem using separability of the cost function and constraint. In this method, a two level strategy is adopted, the lower level solves the economic dispatch problems of the individual units for given power and heat Lambda's and the upper level updates the lambdas by sensitivity coefficients. The procedure is repeated until the heat and power demands are met. Guo *et al*., [3] decomposed the CHPED problem into two sub-problems, that is, heat dispatch and power dispatch. The two sub-problems are connected by the heat-power feasibility constraints of cogeneration units. The analysis and interpretation of the connection have led to the development of a two layer algorithm. The outer layer uses Lagrangian Relaxation technique to solve the power dispatch, and the inner layer uses the gradient searching method to solve the heat dispatch with the unit heat capacity passed by the outer layer. A customized branch and bound algorithm to solve the CHPED problem was developed [4].

Alternatives to the traditional mathematical approaches: An improved penalty function formulation for the genetic algorithm (GA) to solve the CHPED problem was presented [5].Sudhakaran *et al*., [6] employed a hybrid genetic algorithm with tabu search (GT) and applied it to a four-unit system. Subharaj *et al*., [7] proposed a self adaptive real-ended genetic algorithm (SARGA) and successfully applied to solve the CHPED problem. Vasebi *et al*., [1] developed a harmonic search algorithm. Song *et al*., [8] proposed combined heat and power dispatch by improved ant colony search algorithm. In [9], an incorporated algorithm has been developed to solve the CHPED problem. Wang *et al*., [10] proposed multi objective particle swarm optimization for solving CHPED problem. S.S. Sadat Hosseini *et al*., [11] developed mesh adaptive direct search algorithm implemented to solve the CHPED problem with bounded feasible operating region. C.L. Chiang *et al*., [12] proposed a hybrid differential evolution with multiplier updating method to CHPED problem. But these methods did not consider transmission loss and were typically very slow. In order to achieve optimal trade-off between accuracy and performance, hybrid formulations combining classical optimization methods and GA, EP, PSO have been recently reported in the literature. Dorigo *et al*., [13], Eberhart *et al*., [14] and Deneubourg *et al*., [15] discussed about the swarm intelligence of a branch of inspired algorithm and focus on the behavior of insect in order to develop some meta-heuristics algorithms. Exploration and

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exploitation are the important mechanisms in a robust search process. While exploration process is related on independent search for an optimal solution, exploitation uses existing knowledge to bias the search. In the recent years, there are a few algorithms based on the bee foraging behavior developed to improve both exploration and exploitation for solving the optimization problems. The Artificial bee colony (ABC) algorithm introduced in [16] is one approach that has been used to find an optimal solution in numerical optimization problems. This algorithm is inspired by the behavior of honey bees when seeking a quality food source. The performance of ABC algorithm has been compared with other optimization methods such as GA, differential evolution algorithm (DE), Evolution strategies (ES); Particle swarm inspired Evolutionary Algorithm (PS-EA) [17-19]. The comparisons were made based on various numerical benchmark functions, which consist of unimodal and multimodal distributions. The comparison results showed that ABC can produce a more optimal solution and thus is more effective than the other methods in several optimization problems [19-22].

This paper proposes ABC algorithm for solving the CHPED problem. Here, transmission loss is considered. In order to show the validity of the proposed approach, the developed algorithm is illustrated on a single area cogeneration test system (Guo *et al*., 1996). Results obtained from the proposed approach are compared with those obtained from particle swarm optimization (PSO), real-coded genetic algorithm (RCGA) and evolutionary programming (EP). The comparison shows that the proposed ABC based approach achieves lower production cost and CPU time.

2. FORMULATION OF THE CHPED PROBLEM

The system under consideration has power only units, combined heat and power units, and heat- only units. Figure-1 shows the heat-power Feasible Operation Region (FOR) of a combined cycle cogeneration unit. The feasible operation is enclosed by the boundary curve MNOPQR. Along the boundary curve NO, the heat capacity increases as the power generation decreases, the heat capacity declines along the curve OP. The power output of the power units and the heat output of heat units are restricted by their own upper and lower limits. The power is generated by conventional thermal generators and cogeneration units while the heat is generated by cogeneration units and heat-only units. The primary objective of the CHPED is to determine the most economic loading points of combined heat and power generation units such that both the heat and power demands and other constraints can be met within the bonded region in the heat versus power plane.

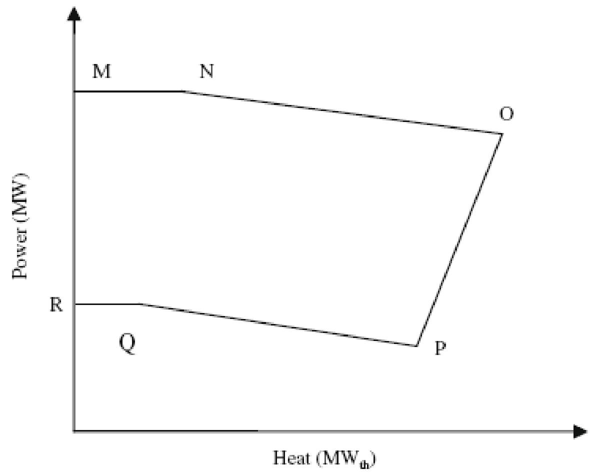

Figure-1.

The objective function of the CHPED problem is given by:

$$\text{Minimize } \left[\sum_{i=1}^{\alpha} F_{ti}(p_i) + \sum_{i=\alpha+1}^{\beta} F_{ci}(P_i, H_i) + \sum_{i=\beta+1}^{n} F_{hi}(Hi)\right] \quad (1)$$

Subject to the equality constraints:

$$\sum_{i=1}^{\alpha} Pi + \sum_{i=\alpha+1}^{\beta} Pi = P_D + P_l \quad (2)$$

$$\sum_{i=\alpha+1}^{\beta} Hi + \sum_{i=\beta+1}^{n} Hi = H_D \quad (3)$$

And inequality constraints

$P_i^{min} \le P_i \le P_i^{max}$ i ε 1, 2….α (4)

P_i^{min} (Hi) ≤ $P_i \le P_i^{max}$ (Hi) i ∈ α+1, α+2…β (5)

H_i^{min} (Pi) ≤ $H_i \le H_i^{max}$ (Pi) i ∈ α+1, α+2…β (6)

$H_i^{min} \le H_i \le$Himax i ∈ β +1, β +2… (7)

The active power transmission loss P_L can be calculated using the network loss formula as:

$$P_L = \sum_{i=1}^{\beta}\sum_{j=1}^{\beta} P_i B_{ij} P_j \quad (8)$$

Where F_{ti}, F_{ci}, F_{hi} are the respective fuel characteristics of the power-only units, cogeneration units and heat only units. P is the unit power generation. H is the unit heat production. i ∈ [1, 2 . . . α] denotes conventional thermal generators. i ∈ [α + 1, α + 2 ...β] denotes cogeneration units .i ∈ [β + 1, β + 2 ...n] denotes heat-only units. The operation ranges of conventional thermal generators and heat- only units are expressed in equations (4), (7) and those for cogeneration units are in equations (5) and (6). The heat and power outputs of the cogeneration units are

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non-separable and one output will affect the other. This mutual dependency of heat and power generation introduced a complication in the integration of cogeneration units. Therefore, the optimization problem of the CHPED is non-linear and highly constrained in nature, H_D and P_D are the system heat and power demands respectively. B_{ij} the loss coefficient for a network branch connected between buses i and j. P^{min} and P^{max} are the unit power capacity limits. H^{min} and H^{max} are the unit heat capacity limits. $P^{min}(H)$, $P^{max}(H)$, $H^{min}(P)$ and $H^{max}(P)$ are the linear inequalities that define the feasible operating region of the cogeneration units.

3. ARTIFICIAL BEE COLONY ALGORITHM

In a real bee colony, some tasks are performed by specialized individuals. These specialized bees try to maximize the nectar amount stored in the hive using efficient division of labor and self-organization. The artificial bee colony (ABC) algorithm, proposed by Karaboga [16] in 2005 for real parameter optimization is an optimized algorithm which simulates the forging behavior of a bee colony. The minimal model of swarm-intelligent forage selection in a honey bee colony which the ABC algorithm simulates consists of three kinds of bees: employed bees, onlooker bees and scout bees. Half of the colony consists of employed bees, and the other half includes onlooker bees. Employed bees are responsible for exploiting the nectar sources explored before and giving information to the waiting bees (onlooker bees) in the hive about the quality of the food sources sites which they are exploiting. Onlooker bees wait in the hive and decide on a food source to exploit based on the information shared by the employed bees. Scout either randomly searches the environment in order to find a new food source depending on a internal motivation or based on possible external clues.

This emergent intelligent behavior in foraging bees can be summarized as follows:

a) At the initial phase of the foraging process, the bees start to explore the environment randomly in order to find a food source.
b) After finding a food source, the bee becomes an employed forager and starts to exploit the discovered source. The employed bee returns to the hive with the nectar and unloads the nectar. After unloading the nectar, she can go back to her discovered source site directly or she can share information about her source site by performing a dance on the area. If her source is exhausted, she becomes a scout and starts to randomly search for a new source.
c) Onlooker bees waiting in the hive watch the dances advertising the profitable sources and choose a sources site depending on the frequency of the dance proportional to the quality of the source.

In the ABC algorithm the position of food source represents a possible solution to the optimization problem, and the nectar amount of a food source corresponds to the profitability (fitness) of associated solution. Each food source is exploited by only one employed bee. In other words, the number of employed bee is equal to the number of food sources existing around the hive (number of solutions in the population). The employed bee whose food source has been abandoned becomes a scout. Using the analogy between emergent intelligence in foraging of bees and the ABC algorithm, the main components of the basic ABC algorithm can be designed as detailed below.

3.1 Initialization of the parameters

The parameters of the basic ABC algorithm are the number of food sources (SN) which is equal to the number of the employed bees or onlooker bees, The colony size is 2*SN (NP), The number of trials after which a food source is assumed to be abandoned (limit), and a termination criterion (MCN). In the basic ABC algorithm, the number of employed bees or the onlookers is set equal to the number of food sources in the population. In other words for every food source, there is only one employed bee.

3.2 Producing initial food source sites

If the search spaces considered being the environment of the hive that contains the food source sites, the algorithm starts with randomly producing food sources sites that correspond to the solutions in the search space. Initial food sources are produced randomly within the range of the parameters defined by:

$$X_{ij} = X_j^{min} + \text{rand}(0, 1)\,(X_j^{max} - X_j^{min}) \quad (9)$$

Where i=1…SN, j=1…D, SN is the number of food sources and D is the number of optimization parameters. In addition, counters which store the number of trials of solutions are reset to zero in this phase. After initialization, the population of the food sources (solutions) is subjected to repeat cycles of the search process of the employed bees, the onlooker bees and the scout bees.

3.3 Sending employed bees to the food sources sites

As mentioned earlier, each employed bee is associated with only one food source site. Hence the number of food source site is equal to the number of employed bees. An employed bee produces a modification on the position of the food source (solution) in her memory depending upon local information (visual information) and finds neighboring food source, and then evaluates its quality. In ABC, finding a neighboring food source is defined by:

$$V_{ij} = X_{ij} + \Phi_{ij}(X_{ij} - X_{kj}) \quad (10)$$

With in the neighboring hood of every food source site represented by X_i, a food source V_i is determined by changing one parameter of Xi. In Equation (10), j is a random in the range [1, D] and k $\in$ {1, 2…SN} is a randomly chosen index that has to be different from i. Φ_{ij} is a uniformly distributed real random number in the range [-1, 1].

As can be seen from Equation (10) as the difference between the parameters of the X_{ij} and X_{kj}

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decreases, the perturbation on the position X_{ij} decreases. Thus, as the search approaches to the optimal solution in the search space, the step length is adaptively reduced. If a parameter value produced by this operation exceeds its predetermined boundaries the parameter can be set to an acceptable value. If the value of the parameter exceed its boundary is set to its corresponding boundaries. If $Xi > X_i^{max}$ then $Xi = X^{max}$; If $Xi < X_i^{min}$ then $X_i = X_i^{min}$. After producing Vi within the boundaries a fitness value for a minimization problem can be calculated to the solution Vi by (11).

$$Fitness_i = \begin{cases} 1/(1+f_i) & \text{if } f_i \geq 0 \\ 1+abs(f_i) & \text{if } f_i < 0 \end{cases} \quad (11)$$

Where f_i is cost value of the solution V_i. For maximization problems, the cost function can be directly used as a fitness function. A greedy selection is applied between X_i and Vi, the better one is selected depending on fitness values representing the nectar amount of the food sources at X_i and V_i. If the source at V_i is superior to that of X_i in terms of fitness values, the employed bees memorize the new position and forget the old one. Otherwise the previous position is kept in memory. If X_i cannot be improved its counter holding the number of trials is incremented by one, otherwise the counter is reset to zero.

3.4 Calculating probability values involved in probabilistic selection

After all employed bees complete their searches, they share their information related to the nectar amount and the positions of their sources within the onlooker bees on the dance area. This is the multiple interaction features of the artificial bees of ABC. Onlooker bees evaluate the nectar information taken from all employed bees and choose a food source site with a probability related to its nectar amount. This probabilistic selection depends on the fitness value of the solutions in the population. A fitness-base selection might be roulette wheel, ranking base, stochastic universal sampling, tournament selection etc. In basic ABC, roulette wheel selection scheme in which each slice is proportional to size to the fitness value is employed in Equation (12).

$$P_i = \frac{Fitness_i}{\sum_{i=1}^{N} Fitness_i} \quad (12)$$

3.5 Food source site selection by onlookers based on the information provided by employed bees

In the basic ABC algorithm, a random real number within the range [0, 1] is generated for each source. If the probability valve (Pi in Equation (12)) associated with that source is greater than this random number then the onlooker bee produces a modification on the position of this food source site by using Equation (10) as in the case of the employed bee. After the source is evaluated, greedy selection is applied and the onlooker bee either memorizes the new position by forgetting the old one or keeps the old one. If solution X_i cannot be improved, its counter holding trial is increased by one; otherwise, the counter is reset to zero. This process is repeated until all onlookers are distributed onto food source sites.

3.6 Abandonment criteria: limit and scout production

In a cycle, after all employed bees and onlooker bees complete their searches the algorithm checks to see if there is any exhausted source to be abandoned. In order to decide if a source is to be abandoned, the counters which have been updated during search are used. If the value of the counter is greater than the control parameter of the ABC algorithm, known as the "*limit*", then the source associated with this counter is assumed to be exhausted and is abandoned. The food source abandoned by its bee is replaced with a new food source is discovered by the scout, which represents the negative feedback mechanism and fluctuation property in the self-organisation of ABC. This is simulated by producing a site position randomly and replacing it with the abandoned one. Assume that the abandoned source is Xi, and then the scout randomly discovered a new food source to be replaced with Xi. This operation can be defined as Equation (9). In the basic ABC, it is assumed that only one source can be exhausted in each cycle, and only one employed bee can be a scout. If more than one counter exceeds the "*limit*" values, one of the maximum ones might be chosen programmatically.

4. ARTIFICIAL BEE COLONY OPTIMIZATION FOR COMBINED HEAT AND POWER ECONOMIC DISPATCH

In this section, an algorithm based on ABC algorithm for solving CHPED problem is described below:

Let $X_i = [P_1, P_2, \ldots P_\alpha, P_{\alpha+1}, P_{\alpha+2}, \ldots P_\beta, H_{\alpha+1}, H_{\alpha+2}, \ldots, H_\beta, H_{\beta+1}, H_{\beta+2}, \ldots H_n]^T$ be the initial vector designating the i^{th} population to be evolved. The elements of X_i are the real power outputs of conventional thermal generators and cogeneration units and heat outputs of cogeneration units and heat-only units. In order to meet exactly the power demand and heat demand dependent power generating unit and heat generating units are selected. Let P_d and H_d be the power output and heat output of the dependent units:

$$P_d = P_D + P_L - \sum_{\substack{i=1 \\ \neq d}}^{\beta} P_i \quad (13)$$

$$H_d = H_D - \sum_{\substack{i=\alpha+1 \\ \neq d}}^{n} H_i \quad (14)$$

The elements of X_i should satisfy the constraints given by Equations (2) - (7). The ABC algorithm implemented to solve CHPED problem is stated in the following steps.

Step 1: Initialization of the control parameters.
The parameters of the basic ABC algorithm are the colony size (NP), the number of food sources (SN=NP/2), the limit for scout, L= SN*D, D is the dimension of the problem and a termination criterion (MCN).

Step 2: Producing initial food source sites.
The initial food sources vector:
$X_i = [P_1, P_2, \ldots P_\alpha, P_{\alpha+1}, P_{\alpha+2}, \ldots P_\beta, H_{\alpha+1}, H_{\alpha+2}, \ldots, H_\beta, H_{\beta+1}, H_{\beta+2}, \ldots H_n]^T$ i=1, 2…NP is determined by Eq. (15) and setting P~U (P^{min}, ^{Pmax}) and H~U (H^{min}, ^{Hmax}), U (a, b) denotes a uniform random variable range over [a, b] and evaluate the fitness value using Equation (16) then select SN the best food source on the basis of highest fitness value as initial food sources and set the cycle = 1, the trail number of each solution X_i, *trial*$_i$, is equal to zero.

Where $X = [X_1, X2 \ldots X_{NP}]$
$X_i = [X_{i,1}, X_{i,2} \ldots X_{i,D}]$

$$\left.\begin{aligned} P_{ij} &= P_j^{\min} + rand(0,1)(P_j^{\max} - P_j^{\min}) \\ H_{ij} &= H_j^{\min} + rand(0,1)(H_j^{\max} - H_j^{\min}) \end{aligned}\right\} \quad (15)$$

$$\text{Fitness}_{(F)} = \frac{1}{\left[\sum_{i=1}^{\alpha} 1 + F_{ti}(Pi) + \sum_{i=\alpha+1}^{\beta} 1 + F_{ci}(Pi, Hi) + \sum_{i=\beta+1}^{n} 1 + F_{hi}(Hi)\right]} \quad (16)$$

Step 3: Sending employed bees to the food sources [SN] and assigning the nectar amount.

In this step each employed bee produces a new solution V_i by using Equation (10) and computes the fitness value of the new solution using Equation (16) satisfying with all constraints. If the fitness of the new one is higher than that of the previous one, the employed bee memorizes the new position and forgets the old one; otherwise the employed bee keeps the old solution.

Step 4: Sending the onlooker bees to the food sources depending on their amount of nectar.

This step required to calculate the probability value P_i of the solution X_i by means of their fitness value using Equation (12). An onlooker bee selects a solution to update its solution depending on the probabilities and determines a neighbour solution around the chosen one. In the selection procedure for the first onlooker, a random number is generated between [0, 1] and if this number is less than P1, the solution is updated using Eq. (10). Otherwise, the random number is compared with P2 and if less than that, the second solution is chosen. Otherwise, third probability of third solution is checked. This process is repeated until all onlookers have been distributed to solutions. The distributed onlooker bee updated its own solution just as the employed bees do.

Step 5: Send the scouts to the search area to discover new food sources.

If the solution Xi is not improved through step 3 and 4, the *trail*$_i$ value of solution Xi will be increased by 1. If the *trail*$_i$ of the solution is more than the predetermined *"limit"* the solution Xi is considered to be an abandoned solution, meanwhile the employed bee will be changed into a scout. The scout randomly produces the new solution by Equation (15) and then compares the fitness of new solution with that its old one. If the new solution is better than the old solution, it is replaced with the old one and set its own *trail*$_i$ into zero. This scout will be changed into employed bee. Otherwise, the old one is retained in the memory.

Step 6: Record the best solution.

In this step, the best solution so far is recorded and increase the cycle by 1.

Step 7: Check the termination criterion.

If the cycle is equal to the maximum cycle number (MCN) then the algorithm is finished; otherwise go to step 3.

The complete flowchart for ABC algorithm is shown in Figure-2.

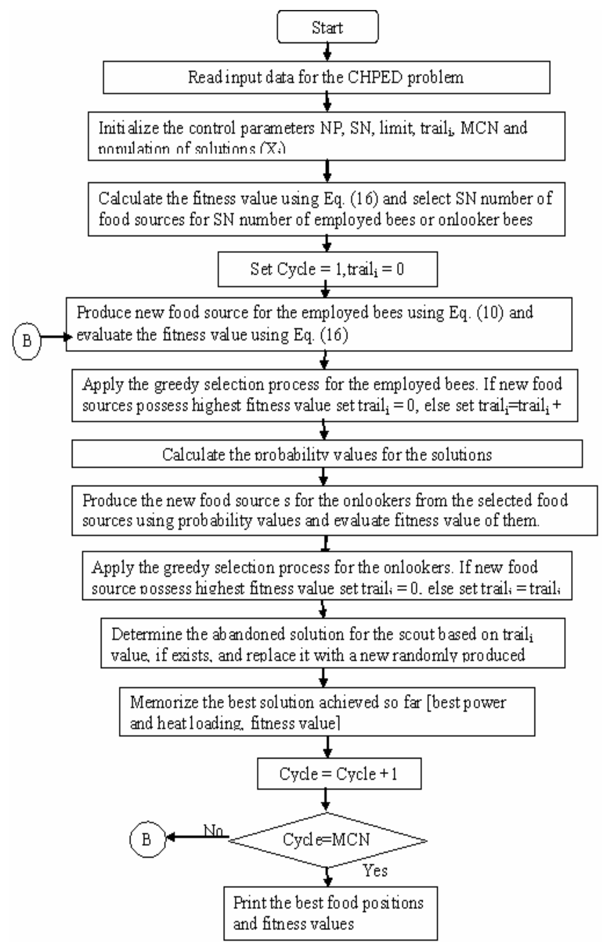

Figure-2.

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5. NUMERICAL RESULTS AND DISCUSSIONS

This section considers a single area cogeneration system to illustrate the effectiveness of the proposed ABC in terms of quality of solution and computation time. The proposed method has been applied to a test system which consists of four conventional thermal generators, two cogeneration units and a heat only unit. Unit data has been modified from (Guo *et al*., 1996 [3]). System data containing valve- point effects coefficients of fuel cost equations and B loss coefficients are obtained from Basu [18]. The feasible operating regions of the two cogenerations units are given in Figures 3 and 4. The system power demand P_D and the heat demand H_D are 600MW and 150MWth, respectively.

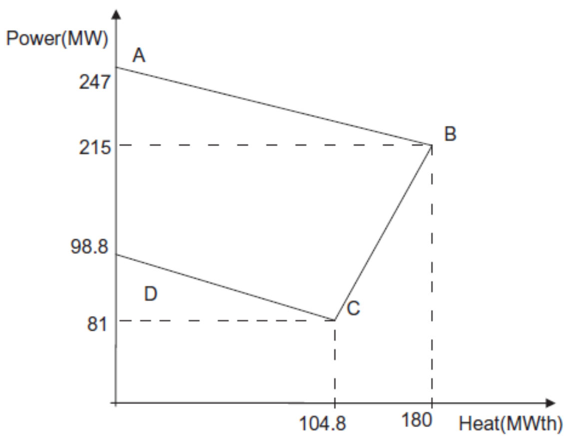

Figure-3.

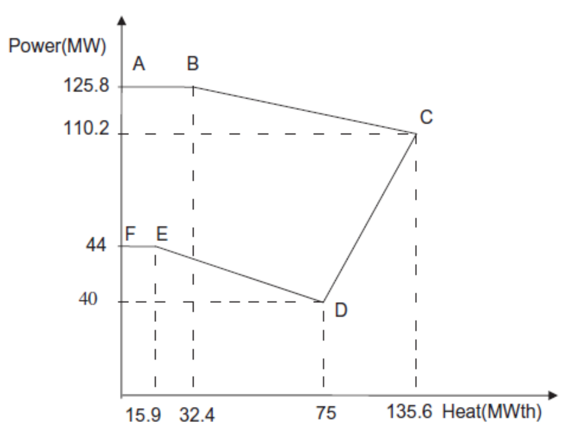

Figure-4.

The fuel cost characteristics of conventional, cogeneration and heat-alone units are given in (18)-(24). The fitness function of the CHPED problem is:

$$\text{Max Fitness}_{(F)} = \frac{1}{[\sum_{i=1}^{4} 1+F_{ti}(Pi)+\sum_{i=5}^{6} 1+F_{ci}(Pi,Hi)+1+F_{h7}(H7)]} \quad (17)$$

Where

a) Power only units:

$$F_{ti}(P_1)=25+2P_1+0.008P_1^2+\left|100\sin\left\{0.042\left(P_1^{min}-P1\right)\right\}\right| \ \$$$

$$10\le P_1\le 75 \text{ MW} \quad (18)$$

$$F_{t2}(P_2)=60+1.8P_2+0.003P_2^2+\left|140\sin\left\{0.04\left(P_2^{min}-P_2\right)\right\}\right| \ \$$$

$$20\le P_2\le 125 \text{ MW} \quad (19)$$

$$F_{t3}(P_3)=100+2.1P_3+0.0012P_3^2+\left|160\sin\left\{0.038\left(P_3^{min}-P_3\right)\right\}\right| \ \$$$

$$30\le P_3\le 175 \text{ MW} \quad (20)$$

$$F_{t4}(P_4)=120+2P_4+0.001P_4^2+\left|180\sin\left\{0.037\left(P_4^{min}-\right)P_4\right\}\right| \ \$$$

$$40\le P_4\le 250 \text{ MW} \quad (21)$$

b) Cogeneration units:

$$F_{c5}(P_5,H_5)=2650+14.5P_5+0.0345P_5^2+4.2H_5+0.03H_5^2+0.031P_5H_5 \ \$ \quad (22)$$

$$F_{c6}(P_6,H_6)=1250+36P_6+0.0435P_6^2+0.6H_6+0.027H_6^2+0.11P_6H_6 \ \$ \quad (23)$$

(c) Heat only unit:

$$F_{h7}(H_7)=950+2.0109H_7+0.038H_7^2 \quad 0\le H_7\le 2695.2 \text{ MWth} \quad (24)$$

Subjected to be equality constraints:

Z1: $P_1 + P_2 + P_3 + P_4 + P_5 + P_6 = P_d$, Z2: $H_5 + H_6 + H_7 = H_d$

And the inequality constraints:

g_1: $1.781914894H_5-P_5-105.7446809 \le 0$,
g_2: $0.1777777784H_5+P_5-247.0 \le 0$
g_3: $-0.169847328H_5-P_5+98.8 < 0$,
g_4: $1.158415842H_6-P_6-46.88118818 \le 0$
g_5: $0.151162791H_6+P_6-130.6976744 \le 0$,
g_6: $-0.067681895H_6-P_6+45.07614213 \le 0$
g_7: $10.0- P_1 \le 0$, g_8: $P_1- 75.0 \le 0$, g_9:$20.0-P_2 \le 0$
g_{10}: $P_2-125 \le 0$, g_{11}=: $30-P_3 \le 0$, g_{12}: $P3-175 \le 0$
g_{13}: $40-P_4 \le 0$, g_{14}: $P_4-250 \le 0$, g_{15}: $0.0-H_7 \le 0$ and
g_{16}: $H_7-2695.2 \le 0$

The Mathematical model consists of nine decision variables (P_1, P_2, P_3, P_4, P_5, H_5, P_6, H_6, H_7) power balance constraint, heat balance constraint and sixteen inequality constraints.

The results obtained from ABC algorithm is compared with PSO [23], RCGA [23], EP [23], and BCO [23]. All these methods are coded in MATLAB 7 and executed using P-1V, 80-GB, 3.0GHZ personal computer. The resulting production costs and CPU time have been used to compare the performance of the ABC with those of other methods. The influence of the ABC parameters-colony size, food source and cycle on the convergence of the algorithm has been studied the colony size has been increased from 10 to 50 in steps of 10 and the iteration varied from 100 to 300. The parameters finally selected for the algorithm for which consistent and superior results with minimum CPU time were found are as follows:

Colony (2*SN), NP=20 number of food source SN=10, MCN=300, Limit value (SN*D)=90. The parameter setting for BCO, EP, PSO and RCGA have been taken from (Basu [23]). Table-1 compares the seven computational results of this test system obtained from ABC, BCO, EP, PSO, RCGA. It is found that the proposed algorithm provides lower production cost and CPU time. Figure-5 shows the cost convergence obtained from ABC, BCO, EP, and PSO. From Figure-5 and Table-1 it can be seen that the best convergence rate as well as the best solution time among the five is obtained from ABC.

Table-1. Results obtained from ABC, BCO, EP, PSO, and RCGA.

	ABC	**BCO [23]**	**EP [23]**	**PSO [23]**	**RCGA [23]**
P1 (MW)	58.7117	43.9457	61.3610	18.4626	74.6834
P2 (MW)	98.5398	98.5888	95.1205	124.2602	97.9578
P3 (MW)	112.6735	112.9320	99.9427	112.7794	167.2308
P4 (MW)	209.8158	209.7719	208.7319	209.8158	124.9079
P5 (MW)	81.000	98.8000	98.8000	98.8140	98.8008
P6 (MW)	40.000	44.0000	44.0000	44.0107	44.0001
H5 (MWth)	23.1014	12.0974	18.0713	57.9236	58.0965
H6 (MWth)	72.2437	78.0236	77.5548	32.7603	32.4112
H7 (MWth)	54.6549	59.8790	54.3739	59.3161	59.4919
Pl (MW)	2.88	8.0384	7.9561	8.1427	7.5808
Cost ($)	10314	10594	10611	10613	10667
CPU time (s)	4.981	5.1563	5.2750	5.3844	6.4723

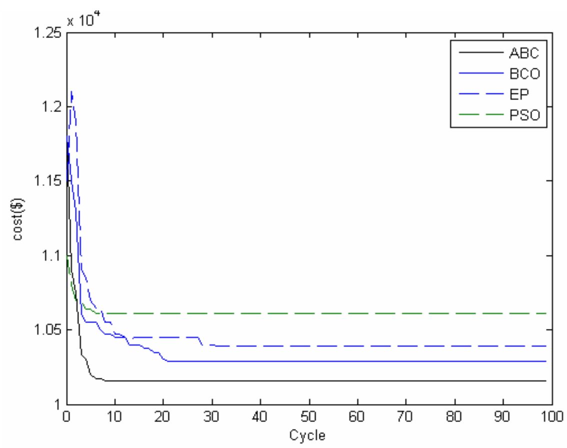

Figure-5.

6. CONCLUSIONS

This paper has presented an algorithm ABC for solving combined heat and power economic dispatch problem. ABC has effectively provided the best solution satisfying both equality and inequality constraints.

REFERENCES

[1] Vasebi A., Fesanghary M. and Bathaee SMT. 2007. Combined heat and power economic dispatch by harmony search algorithm. Int. J. electrical power energy system. 29: 713-719.

[2] Rooijerj Fj. and Amerongen R.A.M. 1994. Static economic dispatch for co-generation systems. IEEE Trans power system. 9(3): 1392-1398.

[3] Gou T. Henwood. and MI. Van Ouijen M. 1996. An algorithm for combined heat and power economic dispatch. IEEE Trans Power System. 11(4): 1778-1784.

[4] Rong A. and Lahdelma R. 2007. An efficient envelope-based branch-and-bound algorithm for non convex combined heat and power production planning. Eur J. oper. Res. 183(1): 1412-1431.

[5] Song Yh. and Xuan QY. 1998. Combined heat and power economic dispatch using genetic algorithm based penalty function method. Int. J. electrical power comp system. 26(4): 363-372.

[6] Sudhakaran M. and Slochanal SMR. 2003. Integrating genetic algorithm and tabu economic dispatch search for combined heat and power. Power System Stability Control. 67-61.

[7] Subbharaj. P., Rengaraj. R. and Salivahanan. R. 2009. Enhancement of combined heat and power economic dispatch using self adaptive real-coded genetic algorithm. Applied energy. 86: 915-921.

[8] Song YH. Chou CS. and Stonham TJ. 1999. Combined heat and power dispatch by improved ant colony search algorithm. Int. J. electrical Power System. Res. 52: 115-121.

[9] Su CT. and Chaiang CL. 2004. An incorporated algorithm for combined heat and power economic dispatch. Int. J. electric power system. Res. 69(2-3): 187-195.

[10]Wang LF. and Singh C. 2008. Stochastic combined heat and power dispatch based on multi-objective particle swarm optimization. Int. J. Electric power Energy system. 30: 226-234.

[11]Seyyed Soheil Sadat Hosseini, Ali Jafarnejad, AmirHossein Behronz and Amir Hossein Gandomi. 2011. Combined heat and power economic dispatch by mesh adaptive direct search algorithm. Expert system with applications. 38: 6556-6564.

[12]C.L Chiang and Chia-AN Wang. 2010. Hybrid differential evolution for cogeneration economic dispatch problem. Proceeding of the 9th conference on Machine Learning and Cybernetics, Qingdao.

[13]Bonbeau E., Dorigo M. and Theraulaz G. 1999. Swarm Intelligence: From natural to artificial systems. New York: Oxford university press.

[14]Eberhart R., Shi Y. and Kennedy J. 2001. Swarm intelligence. San Francisco: Morgan Kaufmann.

[15]Camazine S., Deneubourg J., Franks M.R, Syneyd J., Therayla G. and Bonabeau E. 2003. Self-organisation in biological system. Princeton: Princeton university press.

[16]D. Karaboga. 2005. An idea based on honey bee swarm for numerical optimization. Technical Report_TR06, Ericyes University, Engineering faculty, Computer Engineering Department, Turkey.

[17]D. Karaboga and B. akay. 2009. A comparative study of artificial bee colony, applied mathematics and computation. 214: 108-132.

[18]D. Karaboga and B. Basturk. 2008. On the performance of artificial bee colony (ABC) algorithm. Applied soft computing. 8: 687-697.

[19]A. Singh. 2009. An artificial bee colony algorithm for the leaf-constrained minimum spanning tree problem. Applied soft Computing. 9: 625-631.

[20]F. Kang, j. Li and O.XU. 2009. Structural inverse analysis by hybrid simplex artificial bee colony algorithms. Computers and Structures. 87: 861-870.

[21]N. Karaboga. 2009. A new design method based on artificial bee colony algorithm for digital IIR filters, Journal of the Franklin institute. 346:328-348.

[22]GuoQiang Li., Peifeng Niu. and Xingjun Xiao. 2012. Development and investigation of efficient artificial bee colony algorithm for numerical function optimization. Applied soft computing. 12: 320-332.

[23]Basu. 2011. Bee colony optimization for combined heat and power economic dispatch. Expert system with applications. 38: 13527-13531.

[24]Wang KP and Fung CC. 1995. Simulated annealing based economic dispatch algorithm. Proc Inst Electr. Engg. C. 140: 509-515.

[25]Fogel LJ. Owons AJ and Walsh MJ. 1996. Artificial intelligence through simulated Evaluation. New York: John Wiley and sons.

[26]D. Mitra, F. Romeo and A. Sangiovanni-Vincentelli. 1985. Convergence and finite-time behaviour of simulated annealing. In: proceeding of 24th conference on Decision and Control, Dec. pp. 761-767.

[27]M. Locatelli. 1996. Convergence properties of simulated annealing for continuous global optimization. J. Appl. Probab. 33: 1127-1140.

[28]Karaboga D. and Busturk. B. 2005. A powerful and efficient algorithm for numerical optimization. Ericyes University, Kayseri, Turkey, technical report_Tr06.

[29]Karaboga D. and Busturk B.A. 2007. Powerful and efficient algorithm for numerical function optimization: artificial bee colony optimization. Journal of global optimization. 39: 459-471.