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Improvement of the ACO meta-heuristic by using the method Artificial Bees Colony (ABC)

Abstract. *This paper sets up an Artificial Bee Colony (ABC) algorithm for evolving ant direction Ant Colony Optimization (ACO) to solve the Economic Power Dispatch (EPD) problem. The method ABC-ACO employs the bee colony to find a suitable and the best values operators to improve the ACO. The feasibility of the proposed approach was tested on IEEE 57-bus system. The proposed approach simulation results, which show the effectiveness and robustness of ABC-ACO, have been compared to those that reported in the literature.*

Streszczenie. *W artykule opisano algorytm mrówkowy Artificial Colony Bees (ABC) zastosowany do analizy ekonomicznej rozsyłu energii. Metodę testowano na IEEE 57-magistrali systemowej. Otrzymane wyniki symulacji wskazują na skuteczność i stabilność systemu ABC-ACO. (**Wykorzystanie algorytmu mrówkowego do optymalizacji i analizy ekonomiczne przesyłu energii**)*

Keywords: Economic Power Dispatch (EPD), Artificial Bee Colony algorithm (ABC**),** Ant Colony Optimization (ACO).
Słowa kluczowe: algorytm mrówkowy, analiza ekonomiczna, sieci przesyłowe.

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 method méthaheuristique, The Method Artificial Bee Colony (ABC) to find suitable values of parameters to validate our work we use to solve the problem of Economic Power Dispatch (EPD) 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. The (EPD) problem solution aims to optimize a selected objective function such as fuel cost via optimal adjustment of the power System control variables, while at the same time satisfying various equality and inequality constraints. The equality constraints are the power flow equations [1], while the inequality constraints are the limits on control variables and the operating limits of power system dependent variables. The problem control variables include the generator real powers, the generator bus voltages, the transformer tap settings, and the reactive power of switchable VAR sources, while the problem dependent variables include the load bus voltages, the generator reactive powers, and the line flows. Generally, the EPD problem is a large-scale highly constrained nonlinear optimization problem [2].

This method was tested on the modified IEEE 57 bus test system.

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.

Economic Power Dispatch formulation

Consider a power generation system with i generators.
The Economic Power Dispatch (EPD) problem is to find the optimal combination of power generation that minimizes the total cost while satisfying the total demand. The cost function of EPD problem is defined as follows [3]:

$$Min\left\{ f(P_G) = \sum_{i=1}^{NG} f_i(P_{Gi}) \right\} \tag{1}$$

In Eq. (1), the generation cost function $f_i(P_{Gi})$ in US$/h is usually expressed as a quadratic polynomial.

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

where: $f(P_G)$: Total production cost ($/h); $f_i(P_{Gi})$: is the cost of the *i*th generator in $/h; P_{Gi} *:* The power output of generator i in MW; a_i, b_i, c_i the cost coefficients of the i th generator.
In minimizing the cost, the equality constraint (power balance) and inequality constraint (power limits) should be satisfied.

Equality constraint

$$\sum_{i=1}^{NG} P_{Gi} - \sum_{j=1}^{ND} P_{Dj} - P_L = 0 \tag{3}$$

Where: P_{Dj} : Active power load at bus j, P_{Gi} : Active power generation at bus I; P_L : Real losses.
The transmission loss can be represented by the B-coefficient method [3] as

$$P_L = \sum_i \sum_j P_{Gi} B_{ij} P_{Gj} \tag{4}$$

where B_{ij} is the transmission loss coefficient, P_i, P_j the power generation of *i*th and jth units. The B-coefficients are found through the *Z*-bus calculation technique.

Inequality constraint
The generation capacity of each generator has some limits and it can be expressed as

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

Where: $P_{Gi}^{\min}, P_{Gi}^{\max}$: Lower and upper limit of active power generation at bus I; ND: Number of load buses; NG: Number of generator

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 [4]. Although each ant can build a solution, high quality solutions are only found with this cooperation and information exchange [5].

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 [6].

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. 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 [7]. Different ACO approaches like Ant System, Ant Colony System and Max Min Ant System are available in the literature [8]. 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 $\tau_{ij}(t)=c$ for trail intensity and $\Delta \tau_{ij}=0$
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 $tabu_k(s)$
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 $tabu_k(s)$
4. For k=1 to m do
Move the k-th ant from $tabu_k(n)$ to $tabu_k(1)$
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 ($NC<NC_{MAX}$) 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

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

m: is the total number of ants

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

$P_{ij}^k(t)$: 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 - $tabu_k$}

(8) $$\eta_{ij} = \frac{1}{d_{ij}}$$

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

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.

(10) $$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^k$$

$\Delta\tau_{ij}^k$: 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.

Artificial Bee Colony Algorithm

Artificial Bee Colony (ABC) algorithm, proposed by Karaboga [9] for optimizing numerical problems in, simulates the intelligent foraging behavior of honey bee swarms. An idea based on honey bee swarm for numerical optimization. In ABC algorithm, the colony of artificial bees contains three groups of bees: employed bees, unemployed bees (onlookers and scouts) The scout bees randomly search the enviroment surriounding the hive for new food sources and this bevavior is a kind of fluctuations which is vital for self-organization.

The outlookers waiting in the hive find a food source by means of information presented by employed foragers.

The mean number of scouts is about 5 –10% of the foragers. In ABC, first half of the colony consists of employed artificial bees and the second half constitutes the artificial onlookers. The employed bee whose food source has been exhausted becomes a scout bee[9].

In ABC algorithm, the position of a food source represents a possible solution to the optimization problem and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution. The number of the employed bees is equal to the number of food sources, each of which also represents a site, being exploited at the moment or to the number of solutions in the population.

The main steps of the algorithm are given below [10]:

• Initialize.

• REPEAT.

(a) Place the employed bees on the food sources in the memory;

(b) Place the onlooker bees on the food sources in the memory;

(c) Send the scouts to the search area for discovering new food sources.

• UNTIL (requirements are met).

In the ABC algorithm, each cycle of the search consists of three steps: sending the employed bees onto the food sources and then measuring their nectar amounts; selecting of the food sources by the onlookers after sharing the information of employed bees and determining the nectar amount of the foods; determining the scout bees and then sending them onto possible food sources.

1) Initialize the population of solutions $x_i = (x_{ij})$

2) Evaluate the population

3) cycle=1

4) repeat

5) Produce new solutions (food source positions) v_i in the neighbourhood of x_i for the employed bees; for example using the following formula.

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \quad (11)$$

6) Apply the greedy selection process between v_i *and* x_i .

7) Calculate the probability values *pi* for the solution x_i by means of their fitness values, f_i . For example, using the following equation.

For the minimization problem, the fitness value might be calculated as follows.

$$f_i = \begin{cases} \dfrac{1}{1+F_i} & if \quad F_i \geq 0 \\ 1 + abs(F_i) & if \quad F_i \langle 0 \end{cases} \quad (12)$$

where F_i is the cost value of the objective function.

8) Produce new solutions (new positions) v_i for the onlookers from the solutions x_i , selected depending on *pi* and evaluate them.

9) Apply the greedy selection process between v_i and x_i .

10) Determine the abandoned solution (source) x_i , if exists, and replace it with a new randomly produced solution x_i for the scout. The following definition might be used for this purpose.

$$x_{ij} = x_{\min j} + rand(0,1) \times (x_{\max j} - x_{\min j}) \quad (13)$$

where $x_{\min j}$ is the lower bound of the parameter j and $x_{\max j}$ is he upper bound of the parameter *j*.

11) Memorize the best food source position (solution) achieved so far

12)cycle=cycle+1

13)until (cycle= Maximum Cycle Number (MCN))

Approch ABC-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 factorα, 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 ABC algorithm.

The proposed procedure steps are shown in Fig. 1.

The ACO parameters:

q_0*=0.8;* 1< *β* < *8;* 1< *α* <*8,* ρ= *0.5;* Number of Ants (m) =57. After 30 tests with ACO, using many combinations of parameters values α and *β,* we have chosen the best results (ACO1 *(β = 9,* α=1) **,** *ACO2 (β = 10,* α=2), *ACO4 (β=9.5,*α=4), *ACO5 (β=10* α=5), to compare them with ABC-ACO method, see table 2, it shows clearly that the proposed approach is better in the advantage of saving time to avoid the empirical tests.

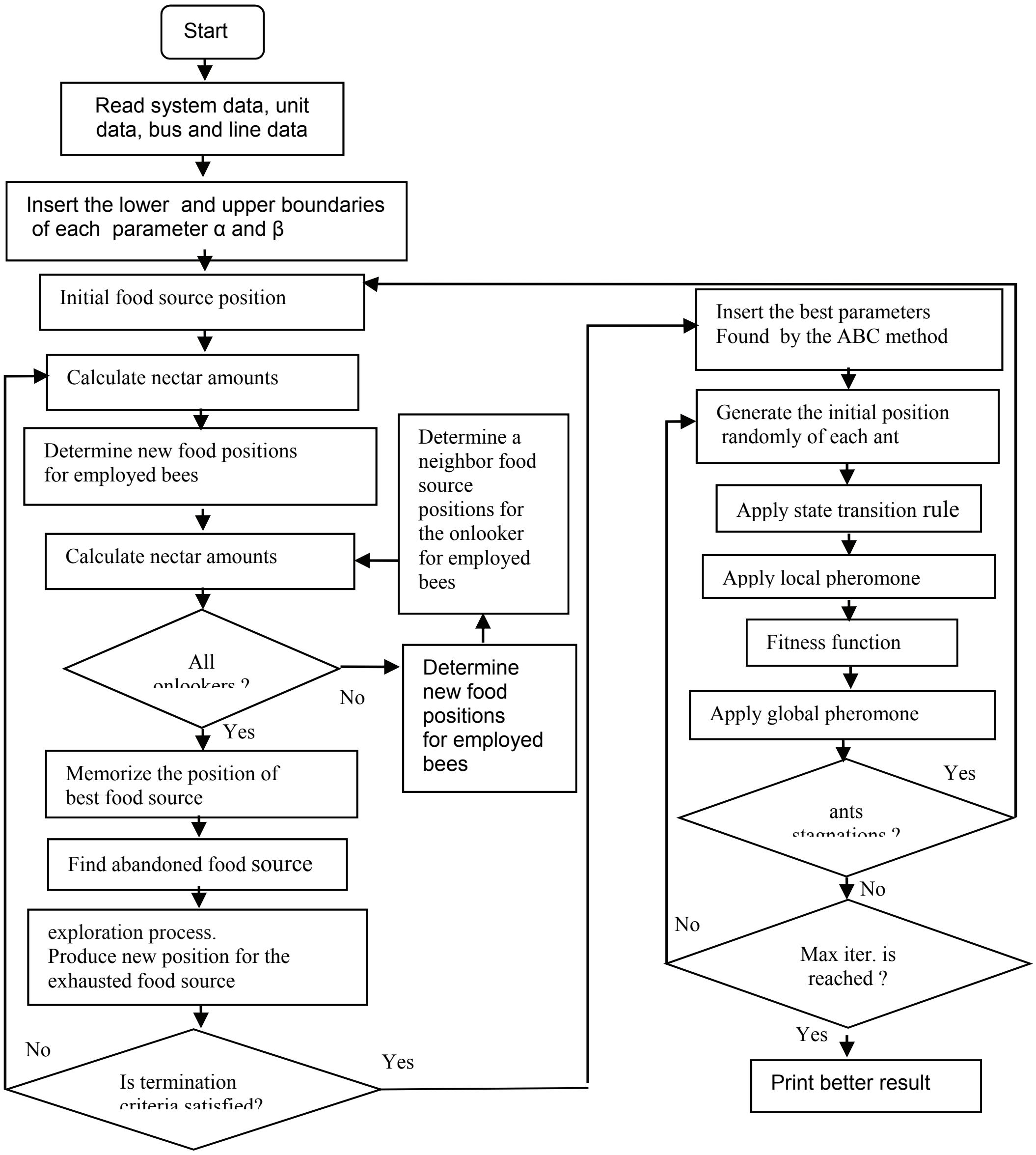

Fig.1. Flow chart for EPD using ABC-ACO.

Simulation Results

In this study, the standard IEEE 57-bus 7-generator test system [12] is considered to investigate the effectiveness of the proposed approach. The values of fuel cost coefficients are given in Table 1, Total load demand of the system is 1250.8 MW, and 7 generators should satisfy this load demand economically. The proposed method is simulated on Pentium IV 2.66 GHz systrm, by using Matlab 6.5. The result obtained from ABC-ACO method is shown in Table 2, 3.

Table 1. Generator operating limits and quadratic cost function coefficients.

Bus No	$P_{Gi}^{\min}$	$P_{Gi}^{\max}$	a_i	b_i	c_i
1	0.00	575.88	0.0776	20.0	0.00
2	0.00	100.00	0.0100	40.0	0.00
3	0.00	140.00	0.2500	20.0	0.00
4	0.00	100.00	0.0100	40.0	0.00
5	0.00	550.00	0.0222	20.0	0.00
6	0.00	100.00	0.0100	40.0	0.00
7	0.00	410.00	0.0323	20.0	0.00

Table 2. Comparison of the five best essays ACO and ABC-ACO applied to an electric network IEEE 57-bus

	ACO1 (β = 9 α=1)	*ACO2 (β = 10* α=2)	*ACO3 (β = 11* α=3)	*ACO4 (β=9.5* α=4)	*ACO5 (β=10* α=5)	ABC-ACO
P1	294.90 1009	332.40 5248	157.22 6487	130.97 4745	222.52 5769	143.98
P2	51.611 821	72.413 114	66.258 656	83.338 227	87.889 167	84.763
P3	33.242 495	47.333 080	32.115 348	18.193 694	67.007 569	43.270
P4	60.463 342	22.368 088	27.002 271	85.461 444	25.804 146	84.773
P5	444.65 4352	390.06 2582	531.69 1815	519.13 6462	446.66 4103	487.61
P6	25.590 000	94.524 960	94.301 337	73.407 397	85.440 488	85.966
P7	356.81 3427	307.85 7217	358.29 2399	356.48 6568	331.66 8242	336.30
Total fuel cost	43717. 54978 5	44897. 20230 0	42332. 82340 5	41882. 23676 9	42426. 87863 6	41676. 34753

Table 3. Results of ACO compared with BFGS, RCGA, GA.QN.D, GA.QN.L and matpower for the IEEE 57-bus system.

	RCGA [11]	BFGS [11]	Hybrid GA.QN.D [11]	Hybrid GA.QN.L [11]	MATPOWER [11]	ABC-ACO
P1	189.93	261.87	140.52	140.53	142.63	143.98
P2	89.73	108.31	86.53	86.41	87.79	84.763
P3	75.13	49.88	43.50	43.53	45.07	43.270
P4	26.35	108.31	86.07	86.43	72.86	84.773
P5	526.36	356.96	487.41	487.33	459.81	487.61
P6	90.94	108.31	87.19	86.42	97.63	85.966
P7	277.93	280.71	336.24	336.30	361.52	336.30
Total fuel cost	42698	43657	41703	41682	41737.79	41676.34
Time (s)	34	6	25	15	0.27	12

Results deliberate by ABC-ACO that is also compared with the real-coded genetic algorithm (RCGA), Broyden-Fletcher-Goldfarb-Shanno (BFGS), hybridization according to Darwin (GA.QN.D), hybridization according to Lamarck (GA.QN.L) and the MATPOWER of the reference [11]. The paper of Naama and al present Hybrid approach to the economic dispatch problem using a genetic. A comparison between the generated active powers calculated by the ACO, RCGA, BCGAs, BFGS , GA.QN.D, GA.QN.L and matpowerfor the IEEE 57-bus system[9]. as well as the costs and the time of convergence has been illustrated in the Table 3.

Conclusion

In this paper a hybrid method for ABC-COA automatically and dynamically adjust the values of the pheromone factor weight α and the weight of heuristic factor that β have a strong influence on the articulation intensification diversification of research in ACO. The purpose is twofold: firstly we aim to free the user of the difficult problem of setting these parameters, we also aim to improve the performance of the overall cost function.

As a study case, the IEEE 57 Bus system with 7 generating units has been selected.

The results using the proposed approach were compared to those reported in the literature. The results confirm the potential of the proposed approach and show its effectiveness and superiority over the

classical techniques and genetic algorithms and the simple ACO

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