# Work-In-Progress: Adaptive Population Artificial Bee Colony for Numerical Optimization

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***Abstract*—In this paper, an adaptive population artificial bee colony (APABC) is proposed. The population size of APABC will be dynamically increased or decreased by population manager according to current solution searching status. Thus, the population size of APABC is not fix but variable. It can enhance bees' searching ability and increase population utilization. In experiments, fifteen test functions of CEC 2005, which include uni-modal and multi-modal functions, are adopted to test the efficiency of proposed method and compare it with original ABC. From the results, it can be observed that the APABC performs better on most test functions.**

***Keywords- adaptive population; artificial bee colony; cross-over; numerical optimization; population manager***

## I. Introduction

In last four decades, there are many classic optimizers were proposed for deal with real-world optimization problems. Such as, genetic algorithm (GA) [1], ant colony optimization (ACO) [2], particle swarm optimization (PSO) [3] and differential evolution (DE) [4] etc.

In 2005, the artificial bee colony (ABC) algorithm was first proposed by Karaboga [5]-[6]. It involves bees' foraging model and simulated bees' forage behavior. The ABC algorithm is consisted of three basic elements, employed bees, onlooker bees and scouts bees. The employed bee and onlooker bee will try to find better food source (better solutions). If both employed and onlooker bees cannot find any food source within limited iterations, then, the scout bee will be activated over for following food searching process for finding new food source.

In recent years, more and more researchers are studying on ABC algorithms either enhancement or applications. In 2012, El-Abd proposed an interesting ABC variant named GOABC [7]. They introduced an opposition-based learning and involved generalized concept into ABC for enhancing optimizer's performance. The GOABC exhibits good results on solving both uni-modal and multi-modal test functions.

In the same year, Yu Liu *et al*. proposed an improved ABC algorithm with mutual learning (mutual learning ABC) [8] whose mutual learning factor will select two bees and to adjust the produced candidate food source with the higher fitness. Besides, Yan *et al*. proposed hybrid artificial bee colony (HABC) algorithm [9], which involved GA's crossover operator to improve bees' information exchange.

In order to improve ABC's convergence performance, recently, Xiang and An proposed efficient and robust artificial bee colony (ERABC) [10]. In ERABC, a combinatorial solution search is proposed to enhance bees' search ability. Also, the chaotic search technique is adopted for scout bee to keep the population diversity and avoid bees being trapped in local optimum. Both strategies can speed up solution searching process.

Although, there are so many ABC variants were proposed. In fact, there is no way to know what suitable population size is for solving current problem until now. In order to solve this problem, in this paper, the population manager is involved to artificial bee colony (ABC) algorithm to increase or decrease population size according current solution searching status.

This paper is consisted of five parts. The basic concept of ABC algorithm is introduced in section II. The detail of proposed method is presented in section III. The experiments results are presented in section IV. Finally, the conclusions are described in section V.

## II. Artificial Bee Colony

Artificial bee colony (ABC) algorithm is a novel numerical optimizer which is to simulate bees' foraging behavior in solution space for finding global optimal solution in reasonable criteria. In ABC, there are two different kinds of bees, which are employed and onlooker bees, will try to find new food source (also called solutions). The food searching process will be performed by following equation.

$$v_{i,j} = x_{i,j} + \emptyset_{i,j} \times \left(x_{i,j} - x_{k,j}\right) \quad (1)$$

where *i* and *k* is a random integer between [1, *ps*], *i* and *k* are two random selected bees and *i* is not equal to *k*. The *ps* represents population size. The *j* is also a random integer between [1, *D*], the *D* denotes dimension of problems. The $\emptyset_{i,j}$ is a normal distribution number between [-1, 1], *x and v* are current food source and new food source, respectively.

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For onlooker bees, food source selection is according to probability which is obtained by equation (2). Similar to employed bees, onlooker bees performs food searching process also use equation (1).

$$p_i = \frac{fit_i}{\sum_{n=1}^{ps} fit_n} \tag{2}$$

where $fit_i$ is fitness value and $i$ denotes the $i_{th}$ bee. The fitness value will be updated by following equation.

$$fit_i = \begin{cases} \frac{1}{(1+f_i)}, & if\ f_i \geq 0 \\ 1 + \mathrm{abs}(f_i), & if\ f_i < 0 \end{cases} \tag{3}$$

where $f_i$ represents objective value of $i_{th}$ bee. If there is no better food source can be found within $g$ generations, the scout bees will then handle the food search process and new food source will be random produced by following equation.

$$x_i^{rand} = lb + rand(0,1)(ub - lb) \tag{4}$$

where $x^{rand}$ denotes a new random produced bee, and $lb$ and $ub$ are the lower and upper boundary of search range respectively.

The procedure of ABC algorithm is listed as follows.

Step 1: Initialization for generated food source randomly.

Step 2: Fitness Evaluations.

Step 3: Employed bees search new food source by (1) and evaluate $x_i$ and $v$ for select better food source.

Step 4: Calculate probability of fitness value by (2).

Step 5: Onlooker bees will select food source by roulette wheel and keep looking for better food by (1).

Step 6: Fitness Evaluations.

Step 7: Record the global best food source (*Gbest*).

Step 8: If there is no better can be found within limited iterations, scout bee will then be activated and try to search new food source.

Step 9: Population manager decrease or increase population size according to current solution searching status.

Step 10: Repeat step 3 to 9, until terminal condition is reached.

## III. Proposed Method

There are several parameters need to be setup before apply the ABC to solve optimization problems, such as reasonable population size. Population contains more bees can extend searching area and increase probability for finding the global optimal solution in solution space, but it will spend more time in iteration and vice versa. Unfortunately, there is no way to know how many bees in the population are suitable for solving current problem until now. It usually depended on users' experience or complexity of the problem.

According to our previous works [11]-[12], the population manager can efficiently improve population utilization for GA and PSO. In this paper, the population manager is involved to ABC, which will increase or decrease bees according to the solution searching status, to enhance ABC's searching ability. Thus, the population size in the proposed method is variable.

Besides, after numerous generations, most bees may be trapped into the local minimum during the searching process, or need a competent guide to lead them toward the potential area. Thus, the information (experience) of existing bees may be too less to handle the current solution searching procedures. Thus, new bees should be joined into the population to speed up the solution searching progress. In order to avoid unlimited increase or decrease in bees, the upper and lower boundary for population size should be predefined.

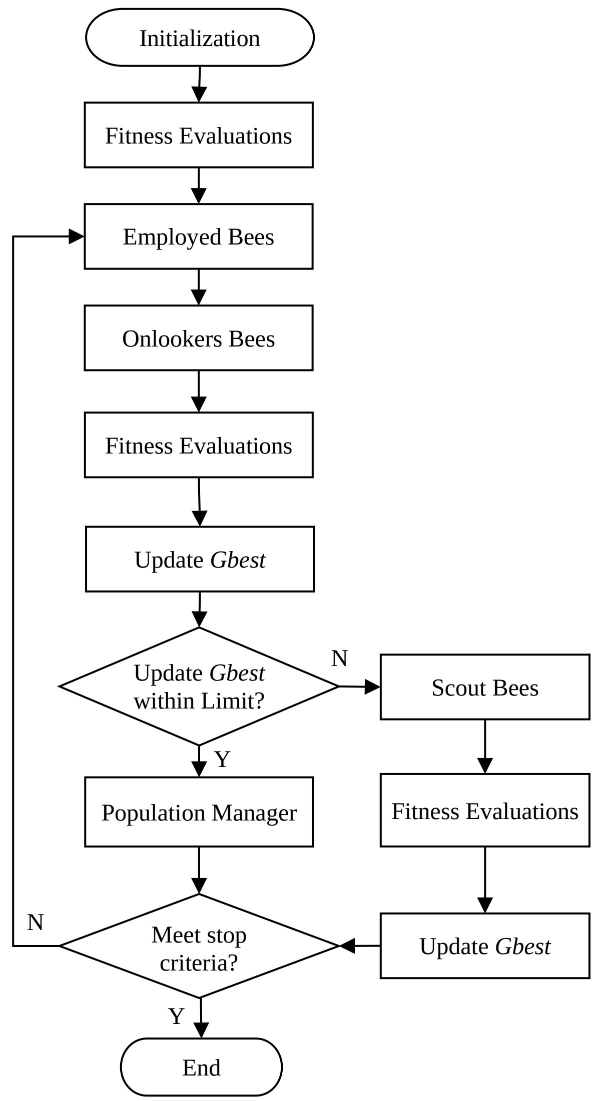


Figure 1. Flowchart of the proposed method

The population manager will adjust population size in following three conditions:

1) If the bees cannot find any better solution in current generation, and the current population size doesn't equal or

exceed the upper boundary. A pair of new bee will be added into the population. The new bees will be created from combining the information of two randomly selected bees, through a crossover-like information combination to provide useful information for these bees. That is, the two newborn bees will be placed at a beneficial position to the population and involved in the solution searching process in the following generation.

2) If the bees can find one or more better solutions in current generation, and the current population size doesn't equal or less than the lower boundary. The existing bees may with ability to handle the current solution searching procedures. The redundant bees should be expelled from the population to conserve their evolution time for speeding up the solution searching progress. Thus, a pair of bees with poor performance in the current iteration will be removed from the population. In the following iteration, the bee number will be two less previous iteration.

3) If current population size reaches the lower or upper boundary, even the bees can find any better solution in current generation or not, the population size will not be changed.

The complete flowchart of the proposed method is shown in Fig. 1. After all bees in the population have moved, the population manager will determine the elimination of a redundant bees with poor performance, generate a pair of bees, or the maintenance of the current population size according to the solution-searching status. All bees in the population will perform the next generation after the population manager.

## IV. Experiments and Results

### A. Test Functions

In order to test the performance of proposed method and compare it with original ABC, fifteen test function of CEC 2005 [13], which include uni-modal functions ($F_1$ ~ $F_5$) and multi-modal functions ($F_6$ ~ $F_{15}$), are selected for experiments. All the test functions are set as 50 dimensions. The names and types of the selected test function are listed in Table I.

TABLE I. Fifteen Selected Test Functions of CEC 2005

| **$f$** | **Test Functions** |
|---|---|
| $f_1$ | Shifted Sphere Function |
| $f_2$ | Shifted Schwefel's Problem 1.2 |
| $f_3$ | Shifted Rotated High Conditioned Elliptic Function |
| $f_4$ | Shifted Schwefel's Problem 1.2 with Noise in Fitness |
| $f_5$ | Schwefel's Problem 2.6 with Global Optimum on Bounds |
| $f_6$ | Shifted Rosenbrock's Function |
| $f_7$ | Shifted Rotated Griewank's Function without Bounds |
| $f_8$ | Shifted Rotated Ackley's Function with Global Optimum on Bounds |
| $f_9$ | Shifted Rastrigin's Function |
| $f_{10}$ | Shifted Rotated Rastrigin's Function |
| $f_{11}$ | Shifted Rotated Weierstrass Function |
| $f_{12}$ | Schwefel's Problem 2.13 |
| $f_{13}$ | Expanded Extended Griewank's plus Rosenbrock's Function (F8F2) |
| $f_{14}$ | Shifted Rotated Expanded Scaffer's F6 |
| $f_{15}$ | Hybrid Composition Function |

The search range and global optimum of all test functions are listed in Table II.

TABLE II. Global Optimum and Search Range of Fifteen Test Functions

| **$f$** | **Global Optimum** | **Search range** |
|---|---|---|
| $f_1$ | -450 | $[-100, 100]^D$ |
| $f_2$ | -450 | $[-100, 100]^D$ |
| $f_3$ | -450 | $[-100, 100]^D$ |
| $f_4$ | -450 | $[-100, 100]^D$ |
| $f_5$ | -310 | $[-100, 100]^D$ |
| $f_6$ | -390 | $[-100, 100]^D$ |
| $f_7$ | -180 | $[0, 600]^D$ |
| $f_8$ | -140 | $[-32, 32]^D$ |
| $f_9$ | -330 | $[-5, 5]^D$ |
| $f_{10}$ | -330 | $[-5, 5]^D$ |
| $f_{11}$ | 90 | $[-0.5, 0.5]^D$ |
| $f_{12}$ | -460 | $[-\pi, \pi]^D$ |
| $f_{13}$ | -130 | $[-3, 1]^D$ |
| $f_{14}$ | -300 | $[-100, 100]^D$ |
| $f_{15}$ | 120 | $[-5, 5]^D$ |

In order to easier compare the performance between both ABCs, the error value $e$ between the real global optimum $f^*$ and function value $f$ found by optimizer will be presented. The error value can be calculated as follows.

$$e = f - f^* \tag{5}$$

### B. Parameters Setting

In the experiments, the original ABC is conducted to compare with the proposed method. In order to fair comparison, all the parameters are according to their original settings. The initial population size of both proposed method and original ABC is set as 250. The upper and lower boundary of population size of population manager is set as 400 and 100 respectively. The maximum Fitness Evaluations (FEs) are set as 500,000.

### C. Experiment Results

In experiments, both APABC and original ABC are executed for 25 independent runs. The experiment results are listed in Table III which presents the mean and standard deviation of error value *e*. The best results among the two ABC variants are shown in bold.

TABLE III. EXPERIMENT RESULTS FOR 50D TEST FUNCTIONS

| Algorithms | Results | $f_1$ | $f_2$ | $f_3$ | $f_4$ | $f_5$ |
|---|---|---|---|---|---|---|
| **ABC** | **Mean** | 9.4884E+02 | 4.7303E+04 | 7.6691E+07 | 4.9125E+08 | 3.1264E+04 |
| | **Std.** | 3.5065E+02 | 4.5119E+03 | 1.0942E+07 | 9.5546E+06 | 2.7450E+03 |
| **Proposed Method** | **Mean** | **1.0429E-09** | **4.5815E+04** | **6.1768E+07** | **8.5348E+07** | **1.6552E+04** |
| | **Std.** | **2.3769E-09** | **6.4391E+03** | **1.0032E+07** | **1.1180E+08** | **1.2760E+03** |
| **Algorithms** | **Results** | $f_6$ | $f_7$ | $f_8$ | $f_9$ | $f_{10}$ |
| **ABC** | **Mean** | 3.3300E+04 | 6.1954E+03 | 2.1275E+01 | 2.2478E+01 | 1.2257E+03 |
| | **Std.** | 3.0981E+04 | 2.1196E-02 | 4.6243E-02 | 2.2991E+00 | 1.2127E+02 |
| **Proposed Method** | **Mean** | **1.1632E+03** | **6.1953E+03** | **2.1272E+01** | **1.2801E+01** | **4.4782E+02** |
| | **Std.** | **3.5480E+03** | **3.4225E-03** | **3.1579E-02** | **2.6700E+00** | **4.9565E+01** |
| **Algorithms** | **Results** | $f_{11}$ | $f_{12}$ | $f_{13}$ | $f_{14}$ | $f_{15}$ |
| **ABC** | **Mean** | 6.4449E+01 | **2.9914E+05** | 1.0990E+04 | **2.3828E+01** | 9.7577E+01 |
| | **Std.** | 3.5780E+00 | **5.0391E+04** | 6.7594E+03 | **1.4140E-01** | 1.4014E+01 |
| **Proposed Method** | **Mean** | **6.2929E+01** | 3.0797E+05 | **6.4127E+00** | 2.3901E+01 | **9.5550E+01** |
| | **Std.** | **2.4482E+00** | 7.9149E+04 | **7.8791E-01** | 1.9907E-01 | **2.8501E+01** |

From the results, it can be observed that the proposed method performed better on all the uni-modal functions, and on most test multi-modal functions. Except the functions 12 and 14, the proposed method performed similar results as original ABC.

## V. CONCLUSIONS

In this paper, the population manager is involved to enhance efficiency of population member's utilization. It can make bees easier to find the better solutions.

Fifteen test functions of CEC 2005, which includes uni-modal and multi-modal functions, were adopted for experiments through a reasonable average and fitness evaluations. From the results, it can be observed that the proposed APABC can find better solutions than original ABC for solving most test functions.


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