Quick Combinatorial Artificial Bee Colony -qCABC- Optimization Algorithm for TSP

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***Abstract*—Combinatorial Artificial Bee Colony Algorithm (CABC) is a new version of Artificial Bee Colony (ABC) to solve combinatorial type optimization problems and quick Artificial Bee Colony (qABC) algorithm is an improved version of ABC in which the onlooker bees behavior is modeled in more detailed way. Studies showed that qABC algorithm improves the convergence performance of standard ABC on numerical optimization. In this paper, to see the performance of this new modeling way of onlookers' behavior on combinatorial optimization, we apply the qABC idea to CABC and name this new algorithm as quick CABC (qCABC). qCABC is tested on Traveling Salesman Problem and simulation results show that qCABC algorithm improves the convergence and final performance of CABC.**

Keywords—combinatorial optimization; swarm intelligence; artificial bee colony

I. INTRODUCTION

Salesman Problem (TSP) is a basic combinatorial optimization problem of many fields such as logistics, transportation and semiconductor industries. This basic problem is about finding a Hamiltonian path with minimum cost and has an NP hard character [1]. Because of the high importance of getting better solutions in acceptable computational times, a lot of scientists applied metaheuristic algorithms to this problem. Some of these algorithms are ant colony optimization (ACO) based methods. In [2], Dorigo and Gambadella used the ant colony system to solve TSP. Zhang and Feng applied a Max-Min ant system to TSP in [3]. Gan et al. proposed an ACO algorithm for TSP in [4] and in this work a scout characteristic is used to solve the stagnation behavior and premature convergence problem of the basic ACO algorithm on TSP. Ilie and Badica improved a new distributed approach for ACO algorithms on a distributed architecture in [5]. Puris, Bello and Herrera applied a Two-Stage approach to improve the quality of the solutions of ACO [6]. Tuba and Jovanovic introduced an improved ant colony optimization algorithm with novel pheromone correction strategy [7]. Bee Colony Optimization (BCO) algorithm is also used for solving TSP by Wong, Low and Chong [8]. Then it is integrated with 2-opt heuristic to improve prior solutions generated by the BCO model [9]. Kim and Cho used a hybrid cultural algorithm with local search for TSP in [10]. Many other bio-inspired methods were developed including Tabu Search [11, 12], Simulated Annealing [13], Particle Swarm Optimization [14, 15], Genetic Algorithms [16, 17], Self Organizing Map [18] to solve TSP. For getting better results hybridizations of these methods especially with local search heuristic algorithms have been also widely used [19, 20, 21].

Artificial Bee Colony (ABC) algorithm is a swarm intelligence based nature inspired algorithm that was introduced by Karaboga for multi-modal and multi-dimensional numeric problems [22, 23]. In [24], a good survey study about ABC algorithm can be examined. Some of the researchers proposed the discrete versions of ABC for TSP. Li et al. described a discrete ABC algorithm that uses the concept of Swap Operator to solve TSP [25]. Li et al. developed an ABC algorithm for TSP by combining the modified nearest neighbor approach and the improved inver-over operation [26]. Combinatorial ABC (CABC) is one of the successful discrete versions of ABC algorithm and applied to TSP problems [27].

The authors introduced a new definition for the foraging behavior of onlooker bees in ABC [28]. In that study they modeled the onlooker bees' behavior more accurately than in the basic ABC and the simulation results showed that this new definition significantly improves the convergence performance of ABC. So, this new version of ABC was named as quick ABC (qABC). In this paper, we incorporate the new definition used in qABC to CABC algorithm used for the combinatorial problems. The rest of the paper is organized as follows; section 2 presents TSP and CABC algorithm is explained in section 3. Section 4 describes the proposed method and the simulation results are demonstrated in section 5 and in section 6, the conclusion is given.

II. TRAVELING SALESMAN PROBLEM

In a basic TSP, a salesman obtains a closed tour so that, he must visit every city once and his start and finish point are the same. While he obtains his closed tour, he tries to achieve minimum cost and the cost of his tour directly depends on the tour length.

In this study, Euclidean distance $d(T[i], T[i+1])$ is used to calculate the distance between the city i and city $(i+1)$ as defined by (1).

$$d(T[i], T[i+1]) = \sqrt{(x_i - x_{i+1})^2 + (y_i - y_{i+1})^2} \qquad (1)$$

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Using the Euclidean distances between the cities, total tour length f can be expressed as fallows (2)

$$f = \sum_{i=1}^{n-1} d(T[i], T[i+1]) + d(T[n], T[1]) \qquad (2)$$

where n is the total number of cities.

III. Combinatorial Artificial bee colony-CABC-algorithm

CABC is a an algorithm introduced as a combinatorial variant of ABC optimization. In CABC, the basic steps of ABC algorithm were used and also, for an effective neighborhood solution searching mechanism, a successful mutation operator of genetic algorithm was adapted to ABC's neighborhood searching approach [27]. This mutation operator was introduced to the literature by Albayrak and Allahverdi [29].

In CABC algorithm, the steps of the employed and onlooker bees' neighbor production mechanisms are:

```
1. Select solution $x_k$ randomly in the population. ($k \neq i$)
2. Select a city $x_i[j]$ randomly.
3. Select the value of searching way parameter $\Phi$ randomly. ($\Phi = \{-1, 1\}$)
4. If ($\Phi = -1$) then
       The city visited before the $x_k[j]$ is set as the before city of $x_i[j]$.
   Else
       The city visited after the $x_k[j]$ is set as the after city of $x_i[j]$.
   End if // This operation produces a new closed tour $T^{\#}$.
5. When this new connection is obtained there will be an open sub tour $T^*$. This sub tour's first city is assigned as $R_1$ and last city as $R_2$.
6. If ($random \leq P_{RC}$) then
       Add $T^*$ to $T^{\#}$ so that a minimum extension is generated.
   Else
       If (random $\leq P_{CP}$)
           ▪ Add each city of $T^*$ to the $T^{\#}$ starting from the position $R_1$ by rolling or mixing with $P_L$ probability.
       Else
           ▪ Select randomly one neighbor from neighbor lists for the points $R_1$ and $R_2$ ($NL_{R1}$ and $NL_{R2}$)
           ▪ Invert the points $NL_{R1}$ or $NL_{R2}$ that provides maximum gain such a way that these points will be neighbors to the points $R_1$ or $R_2$.
           ▪ Repeat if the inversion is not taken place.
       End if
   End if
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$x_i[j]$ notation represents the position of the city j in solution i. *random* is a random generated number in (0,1). T is the original tour that represents the solution x_i without any neighborhood searches. GSTM parameters: P_{RC} is reconnection probability, P_{CP} is the correction and perturbation probability, P_L is linearity probability and minimum sub tour length is given as L_{MIN}, maximum sub tour length is L_{MAX}, neighborhood list size is NL_{MAX}.

The point R's gain G_R is calculated by using (3).

$$\begin{aligned} G_R &= d[T[R], T[R+1]] + d[T[NL_R], T[NL_R+1]] \\ &\quad - (d[T[R], T[NL_R]] + d[T[R+1], T[NL_R+1]]) \end{aligned} \qquad (3)$$

IV. Quick Combinatorial Artificial bee colony - qCABC- Algorithm

In real honey bee colonies, employed bees and onlooker bees determine their food sources in different ways. Employed bees exploit the food sources which they have already visited before. However, an onlooker is affected by the dances of employed bees and decides a region of food sources to exploit, which she has not visited before. When she arrives at that region, she visually examines the sources from above and chooses the fittest one. In other words, she evaluates the information of sources which have a similarity in terms of position, before making a decision since she visits the region first time. However, in basic ABC algorithm, employed and onlooker bees determine their food sources by using the same formula. Therefore, Karaboga and Gorkemli introduced a new definition for the onlooker bees and described qABC in [28] and used qABC model for numerical optimization problems. If an appropriate similarity measure for the solutions in CABC is defined as in qABC, this useful idea can be incorporated into CABC proposed for combinatorial problems. Details of the qABC algorithm can be found in [28].

In this study we define a similarity measure for TSP solutions to use the new definition for the onlooker bees in CABC algorithm and then call this new CABC as qCABC . Instead of using the Euclidean distance proposed for numerical optimization in qABC, the distance between two solutions x_i *and* x_m is defined by (4) and (5) in TSP,

$$\begin{aligned} dv_{im}(j) &= 0, \quad if\ (x_i[j].afterCity = x_m[j].afterCity\ \ or \\ &\qquad\qquad x_i[j].afterCity = x_m[j].beforeCity) \\ dv_{im}(j) &= 1, \quad else\ not \end{aligned} \qquad (4)$$

where dv_{im} is a distance vector for the two closed tours x_i *and* x_m . This definition of similarity is about the same connections of the cities in the closed tours. And the total distance between two solutions, $d(i,m)$ is calculated by using (5)

$$d(i,m)=\sum_{j=1}^{n-1} dv_{im}(j) \tag{5}$$

Steps of qCABC algorithm are follows:

```
1. Initialize the parameters: colony size $cs$, maximum number of iterations $MaxNumber$.
2. Initialize the positions of the food sources $x_i$. $i = 1, 2,\ldots, cs$.
3. Evaluate the population of solutions.
4. Memorize the best solution.
5. $c = 0$
6. REPEAT
   • Employed bees phase: for each employed bee;
       o Produce a new solution $\upsilon_i$ in the neighborhood of $x_i$ and evaluate it.
       o Apply the greedy selection process between $x_i$ and $\upsilon_i$.
   • Calculate the probability values $p_i$ for the solutions $x_i$ by using their fitness values with (6).

         $p_i = \frac{0.9 \times fit_i}{fit_{best}} + 0.1$        (6)

   • Onlooker bees phase: for each onlooker;
       o Depending on $P_i$ select a solution $x_i$.
       o Considering the neighborhood radius $r$, determine the best solution $x_{N_m}^{best}$ among the neighbors of the solution $x_i$ and itself.
       o Produce a new solution $v_{N_m}^{best}$ from $x_{N_m}^{best}$ and evaluate it.
       o Apply the greedy selection process between $x_{N_m}^{best}$ and $v_{N_m}^{best}$.
   • Memorize the best solution achieved yet.
   • Determine the abandoned solution, if exists, replace it with a new randomly produced solution for the scout.
   • $c = c + 1$
7. UNTIL $c = MaxNumber$.
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Notice that there is only one difference between CABC and qABC algorithms, which is related to the onlooker bees phase. While, in CABC, employed and onlooker bees determine their new solutions in the same way, in qCABC, they use different definitions.

Since the aim of TSP optimization is minimizing the total closed tour length, the quality of each solution fit_i is calculated by using (7)

$$fit_i = \frac{1}{1+f(x_i)} \tag{7}$$

where $f(x_i)$ is the tour length of the solution x_i.

For the limit value, l is calculated by (8)

$$l = \frac{cs \times D}{3} \tag{8}$$

where cs refers the colony size and D represents the dimension of the problem ($D = n$).

V. Simulation Results

In this study, the performance of qABC is evaluated on two benchmark problems and the results are compared with nine different optimization methods in the literature (eight different genetic algorithms having different mutation operators in [29] and CABC algorithm). The first test problem is KroB150. This problem has 150 cities and the optimum tour length of KroB150 is 26130. The second benchmark is KroA200. It contains 200 cities and the optimum tour length for this problem is 29368. These problems and optimum tour lengths can be found in the TSPLIB: http://www.iwr.uni-heidelberg.de/groups/comopt/software/TSPLIB95/. Distances between the cities were measured by integer numbers.

For a fair comparison, initial solutions were produced by Nearest Neighbor tour construction heuristic and the same parameter values are taken as in [29]. Considering the searching mechanisms of CABC and qCABC algorithms, the parameter L_{MAX} is set as $n/2$, not Int(sqrt(n)) as in [29]. Table 1 shows the parameter settings of CABC and qCABC algorithms. We carried out 10 runs for each problem with random seeds.

TABLE I. Parameter Settings

Parameter	CABC	qCABC
cs	40	40
$MaxNumber$	20000	20000
P_{RC}	0.5	0.5
P_{CP}	0.8	0.8
P_L	0.2	0.2
L_{MIN}	2	2
L_{MAX}	$n/2$	$n/2$
NL_{MAX}	5	5
r	-	1

The performance comparison of qCABC, CABC and different genetic algorithms is given in Table 2. In order to consider the results presented in [29], in this comparison the best and average percentage error values are used. These percentage errors are calculated by (9)

$$Error(\%) = \frac{L_F - L_O}{L_O} \times 100 \tag{9}$$

where L_F represents the tour length found by the algorithm and L_O is the optimum tour length for the problem.

When the table is examined, the success of CABC and qCABC algorithms can be seen clearly. Especially qCABC algorithm gives the best results in terms of best error for the problems. The convergence graphics of CABC and qCABC are shown in Fig. 1-2 for the first 2000 cycles of the optimization. These figures demonstrate that qCABC is quicker than CABC.

TABLE II. PERFORMANCE COMPARISON OF GA AND CABC ALGORITHM

Methods	KroB150		KroA200	
	Best Error(%)	***Ave. Error(%)***	***Best Error(%)***	***Ave. Error(%)***
EXC	2.9277	5.0919	2.5061	4.9877
DISP	7.8263	10.4635	6.7284	8.8276
INV	7.1183	9.0521	6.2245	8.3594
INS	1.8178	4.5488	2.1554	4.2819
SIM	2.8397	3.8596	1.5766	3.2457
SCM	3.2836	7.0609	3.9873	5.4502
GSM	3.4520	4.9541	4.4675	5.7018
GSTM	0.9644	1.7616	0.8683	1.5432
CABC	0.3100	**0.6950**	0.4597	0.6034
qCABC	**0.0574**	0.7853	**0.4222**	**0.5145**

VI. CONCLUSIONS

In this paper, a new version of combinatorial ABC algorithm is introduced for solving TSP. The new version is called quick Combinatorial ABC -qCABC algorithm. qCABC is tested on two TSP benchmarks with 150 cities and 200 cities. Experimental results showed that our new algorithm -qCABC- presents good solutions for the considered problems. As future work, we plan to evaluate the performance of new CABC on more test problems and also to analyze the effect of control parameters on the performance of the algorithm.

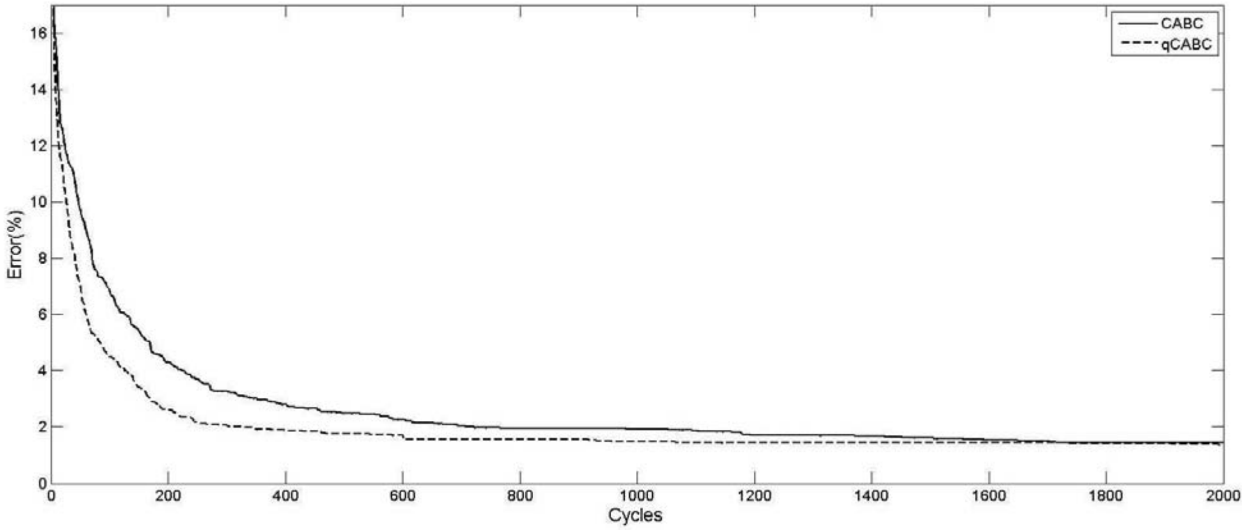

Figure 1. Convergence performance of CABC and qCABC algorithms on KroB150 problem

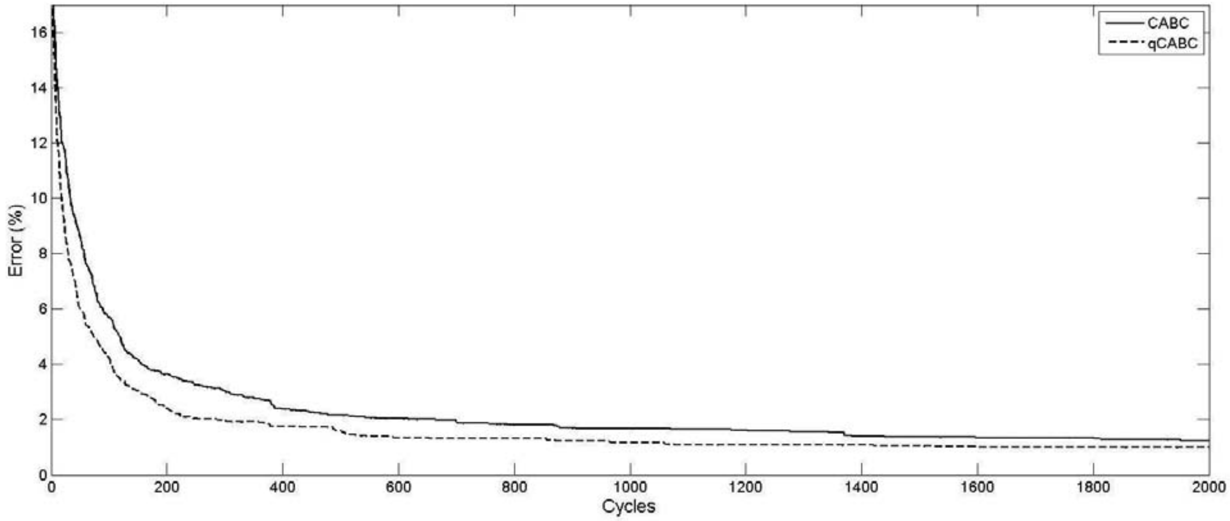

Figure 2. Convergence performance of CABC and qCABC algorithms on KroA200 problem

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