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Research Article
Ant Colony Optimization: Approach for an Obstacle

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Abstract

This study presents a robust optimization algorithm based on updating Ant Colony Optimization (ACO) through hybridization with Artificial Bee Colony (ABC) method and information exchange concept for the purpose of covering ACO limitations in case of an obstacle was on the ant's path to food source. The global optimal solution found by the proposed hybrid ACO and ABC (ACOBC) algorithm is considered to be as novel technique to find the shortest path when the vision to food source location is not clear because of an obstacle. Both of the ACO and ABC methods share the globally best solutions through the information exchange process between the ants and bees. Based on the results, the exchange process significantly increases exploration and exploitation of the hybrid method. Besides, a focused elitism scheme is introduced to enhance the performance of the developed algorithm. The validity of the ACOBC method is verified using several continuous test problems and a typical discrete problem, called Traveling Salesman Problem (TSP). The proposed method is found to be a competitive optimization tool for solving continuous and discrete problems. Obstacle model study is very important due to its significance in solving many complex networking problems connected to real human life situations where real data are not available.

Key words: Global optimization, ant colony optimization, artificial bee colony, obstacle, traveling salesman problem

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INTRODUCTION

Optimization is the choice of a vector for an objective function in a given domain to make an optimal solution. In the last two decades, several meta-heuristic techniques have been developed to solve difficult optimization problems. Some of these problems are reliability (Zou *et al*., 2010, 2011a), feature selection (Li and Yin, 2013a), knapsack (Zou *et al*., 2011b), face detection (Owusu *et al*., 2014), scheduling (Li and Yin, 2013b), pattern recognition (Kumar and Rani, 2013), economic load dispatch (Zhisheng, 2013), classification (Diao *et al*., 2012) and image segmentation (Zhang *et al*., 2011). The potential of meta-heuristic optimization approaches for addressing various maximization/minimization problems is well-understood. This is evident from the sizeable number of recently proposed modern stochastic optimization methods (Yang *et al*., 2012; Gandomi *et al*., 2013d).

Some of the major meta-heuristic optimization methods that have been applied to solve challenging optimization problems are: Differential Evolution (DE) (Storn and Price, 1997; Gandomi *et al*., 2012; Li and Yin, 2012), Bat Algorithm (BA) (Yang and Gandomi, 2012; Gandomi *et al*., 2013c; Yang, 2010; Mirjalili *et al*., 2014c), genetic algorithms (GAs) (Goldberg, 1989; Manurung *et al*., 2012), Evolutionary Strategy (ES) (Beyer and Schwefel, 2002), Artificial Bee Colony (ABC) (Karaboga and Basturk, 2007), Genetic Programming (GP) (Gandomi and Alavi, 2011), fruit fly optimization algorithm (Pan, 2012), Animal Migration Optimization (AMO) (Li *et al*., 2014), Artificial Plant Optimization Algorithm (APOA) (Cai *et al*., 2012), artificial physics optimization (Xie *et al*., 2012), Probability-Based Incremental Learning (PBIL) (Baluja, 1994), Grey Wolf Optimizer (GSO) (Mirjalili *et al*., 2014a), Biogeography-Based Optimization (BBO) (Simon, 2008; Mirjalili *et al*., 2014b), Harmony Search (HS) (Geem *et al*., 2001; Yadav *et al*., 2012), Flower Pollination Algorithm (FOA) (Yang *et al*., 2014), Particle Swarm Optimization (PSO) (Mirjalili and Lewis, 2013; Kennedy and Eberhart, 1995; Talatahari *et al*., 2013; Mirjalili *et al*., 2012), Charged System Search (CSS) (Kaveh and Talatahari, 2010), Ant Colony Optimization (ACO) (Dorigo and Stutzle, 2004) and Cuckoo Search (CS) (Gandomi *et al*., 2013a, b; Yang and Deb, 2009).

Ant Colony Optimization (ACO) is a meta-heuristic in which a colony of artificial ants cooperates in finding good solutions to difficult discrete optimization problems. The ACO obstacle approach problem is a good model for combinational optimization, where many of such problems are considered to be as NP-hard, though it is very important to find very quick and high-quality solution (Dorigo and Stutzle, 2004).

On the other side, the ABC algorithm, motivated by the swarm behaviours of bee colonies has a quite simple yet effective structure for solving optimization problems (Karaboga and Basturk, 2007). Hence, it has attracted the attention of many researchers.

It is known that the meta-heuristic methods require various exploration and exploitation schemes for solving problems with increasing dimensions in the search space. Although, the ACO generally explores the search space well and appears to be fully capable of locating the global optimal value, its exploration ability has exhibited relatively poor performance at later run phase; especially in the obstacle case where the food source location on the other side of the obstacle is obscure and in the case of arising new shorter path but the ants won't change its path (Dorigo and Stutzle, 2004). On the other hand, the ABC method has strong exploration ability with its poor exploitation (Zhu and Kwong, 2010). Therefore, single ACO or ABC method seems not to be efficient for the exploration and exploitation of the search space. To cope with this issue, this study presents a hybridization of the ABC and ACO methods for solving continuous numerical global optimization as well as discrete problems that optimally solves obstacle model.

MATERIALS AND METHODS

ACO method: Examples of meta-heuristics include simulated annealing (Cerny, 1985; Kirkpatrick *et al*., 1983), tabu search (Glover, 1989, 1990; Glover and Laguna, 1997), iterated local search (Lourenco *et al*., 2002), evolutionary computation (Fogel *et al*., 1966; Holland, 1975; Rechenberg, 1973; Schwefel, 1981; Glover, 1989). In formally, an ACO algorithm can be imagined as the interplay of three procedures.

Construct ants solutions, update pheromones and Daemon actions, where the work of every procedure is clear from its name without going into more details.

Many ACO algorithms have been suggested in this field, we will proceed with the most successful algorithm; "Ant Colony System (ACS)" (Dorigo *et al*., 2006). The ACS mechanism adds a local pheromone (update) at the end of each constructed solution step. Local pheromone update is performed by all ants to diverse solution in every iteration through decreasing pheromone and ultimately to give subsequent ants a chance to search for different solutions. The formula of local pheromone updated in Eq. 1:

$$\mu_{k1} = (1-\varphi)\mu_{kl} + \varphi\mu_0 \quad (1)$$

where, φ denotes pheromone evaporation and μ_0 is the initial value of pheromone.

In addition to local pheromone update, ACS performs pheromone update at the end of each iteration by only one ant which can be either the iteration-best or the best-so-far. Update formula in Eq. 2:

$$\mu_{k1} \leftarrow \begin{cases} (1-\rho)\mu_{kl}+\rho\,\Delta\mu_{kl} & \text{if (i, j) belongs to best tour otherwise} \\ \mu_{kl} \end{cases} \tag{2}$$

where, $\Delta\mu_{kl} = 1/L_{best}$ and L_{best} is the tour length of best ant that can be found either in the current "Iteration-best" or "Best-so-far" or combination of both.

ACO obstacle approach problem is a good model for combinational optimization, where many of such problems are considered to be as NP-hard, though it is very important to find very quick and high-quality solution.

ABC method: Artificial Bee Colony is one of the seminal meta-heuristic methods among various intelligent optimization techniques. After the appearance of swarm intelligence of bee colony, the forage selection is modeled. Based on this model, the definition of three main concepts can be defined as follows (Zhang and Wu, 2012):

- **Food resource:** In the simplest form, the value of a food source is described with only one quantity. Figure 1 represents two food resources and two non-food resources, respectively. Furthermore, S, O, R, UF and EF denote scouts, onlookers, recruits, unemployed foragers and denote employed foragers, respectively
- **Unemployed foragers:** The unemployed forages have two sorts. One is Scouts (S). A scout bee is type of bee that begins implementing search autonomously without any a priori knowledge

The other one is Onlookers (O). They only stay in the nest in order to search for a food source with the help of the employed foragers.

- **Employed foragers:** All of them are related to a food source that they are exploiting now. This information is

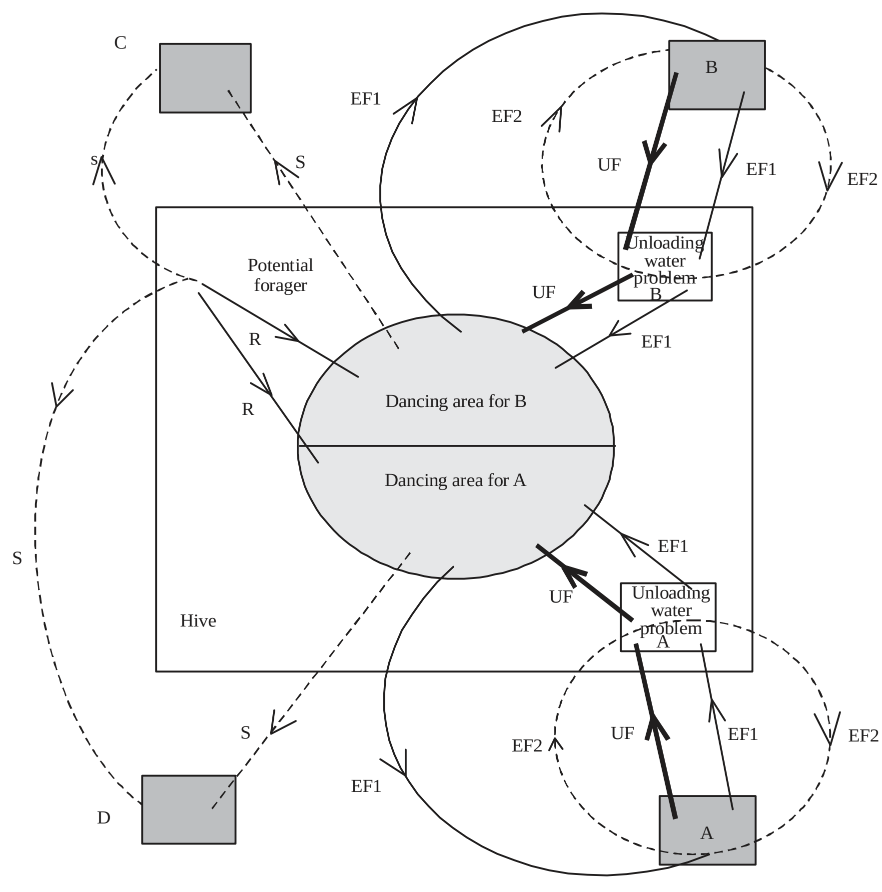

Fig. 1: Bee colony

shared with some probability. Three feasible choices associated with the quantity of nectar are provided for the foraging bee

- **One is Unemployed Forager (UF):** When the nectar is less than a fixed threshold, the foraging bee gives it up and turns to an unemployed bee
- **Employed Forager 1 (EF1):** If not, it may dance and recruit mates. The last one is Employed Forager 2 (EF2). It may forage around the food source all the time (Karaboga and Basturk, 2008)

The artificial bee colony includes three types of bees: (1) Employed bees, (2) Onlookers and (3) Scouts. In the artificial bee colony, a food source corresponds to an employed bee. That is to say, the employed bees and the food sources have the same number. The detailed main steps of the search conducted by the artificial bees can be described as follows (Sabat *et al*., 2010):

Step 1: Initialize the population x_{ij}
Step 2: Repeat
Step 3: Generate new solutions v_{ij} around x_{ij} for the employed bees as in Eq. 3:

$$v_{ij} = x_{ij}+\Phi\ (x_{ij}-x_{kj}) \tag{3}$$

Here, k is a solution around i, Φ is a random number [-1, 1].

Step 4: The greedy selection is used between x_i and v_i
Step 5: Calculate the probability P_i for x_i according to their fitness as in Eq. 4:

$$P_i = \frac{f_i}{\sum_{i=1}^{SN} fi} \tag{4}$$

SN is the number of food sources and f_i is its fitness.

Step 6: Normalize P_i into [0, 1]
Step 7: Generate the new solutions v_i for the onlookers from x_i, selected depending on P_i
Step 8: The greedy selection is used for the onlookers between x_i and v_i
Step 9: Check if a solution is abandoned. If it is, replace it with a novel one x_i for the scout as in Eq. 5:

$$x_{ij} = min_j+\Phi_{ij}\ (max_j-min_j) \tag{5}$$

Here, Φ_{ij} is a random number in [0, 1].

Step 10: Save the best solution obtained up to now
Step 11: Go to Step 2 until termination criteria is satisfied

ACOBC method: Based on the above-analyses of the ACO, when the ants gets trapped in the local values, it cannot escape from local minimum by itself, also the ants cannot know by itself the shorter path to food source located on the other side of the obstacle.

Further, ABC algorithm does not directly utilize the global optimal individual. To overcome these limitations, a hybrid meta-heuristic method based on information exchange is presented. The hybridization process is similar to that proposed by Kiran and Gunduz (2013).

Information exchange or crossover operation is one of the most famous evolution operators. Here, it is used for yielding a new solution, called The Best.

The Best is considered to be Abest for the ACO and food source of onlooker bees for the ABC. To get TheBest, the Abest of the ACO and the optimal individual of the ABC are computed by Eq. 4. Probabilities used to select the two solutions are given by Eq. 6 and 7:

$$P_{best} = \frac{fit_{best}}{fit_{Abest} + fit_{best}} \tag{6}$$

where, P_{best} is the probability to choose the optimal individual of the ABC, fit_{best} and fit_{Abest} are the Abest of the ACO and the optimal individual of the ABC achieved according to Eq. 4:

$$P_{Abest} = \frac{fit_{Abest}}{fit_{Abest} + fit_{best}} \tag{7}$$

where, P_{Abest} is the Abest of the ACO.

When generating the best solution, random numbers in the range of [0, 1] are utilized for the dimensions of the standard test function. If it is not above P_{best}, the value for this dimension is selected from the optimal individual of ABC. Otherwise, this value is selected from Abest of ACO. This selection process can be formulated as Eq. 8:

$$\text{The Best}_i = \begin{cases} Best_i & \text{if } r < P_{best} \\ Abest_i & \text{otherwise} \end{cases} \tag{8}$$

where, The $Best_i$ is the i-th dimension of The Best. The $Best_i$ is i-th dimension of The Best solution found by ABC, A $best_i$

is the i-th dimension of Abest of the ACO. The r is a random number in the range of [0, 1]. Based on the information exchange described above, the connection between the ants and bees in the ACOBC method can be stated as follows:

- The global part of the ACOBC method is "The Best". Through The Best, not only ACO has enhanced the ability of escaping from local minima but also the exploitation of ABC is significantly enhanced by the direct utilization of the global best solution.
- Abest of the ACO is updated in terms of The Best accordingly and the same is passed on to onlooker bees of ABC as neighbor.
- Besides, a concentrated elitism strategy is introduced into ACOBC to forbid the optimal solutions from being ruined by the method. This is done to guarantee that the whole population is capable of proceeding with a better status than before. By introducing this concentrated elitism strategy into the algorithm, the ACOBC has been further developed.

RESULTS AND DISCUSSION

Bench mark evaluation: In order to validate ACOBC, it has been applied to optimize a series of benchmark functions from previous studies presented in Table 1 (Yang *et al*., 2013; Wang *et al*., 2014b). In order to conduct a fair comparison, all the simulations were implemented on the same environments (Wang *et al*., 2013; Guo *et al*., 2014).

Here, the performance of ACOBC was compared with nine nature-inspired methods viz. ABC (Karaboga and Basturk, 2007), ACO (Dorigo and Stutzle, 2004), DE (Storn and Price, 1997), ES (Beyer, 2001), GA (Goldberg, 1989), HS (Geem *et al*., 2001), KH (Mousavi *et al*., 2013), PBIL (Baluja, 1994) and PSO (Kennedy and Eberhart, 1995). Furthermore, Dumitrescu and Stutzle (2004) performance was the overall best performance, with respect to the number of best known solutions found was obtained by ACS. Therefore, ACS is selected as the representative of ACO algorithm.

For ACO and ACOBC, the same parameters are suggested as well as for the other methods parameters are set suggested in the study of Wang *et al*. (2014a-c).

It is well-known that most of the meta-heuristic methods are based on certain type of stochastic distribution. To obtain typical performances, three-hundred trials are implemented for each method on each function (Table 2 and 3). Different standards are considered to normalize values in the tables. Therefore, values are not comparative between each other (Wang *et al*., 2014c). The dimension of the benchmark is set thirty. From Table 2, it can be seen that ACOBC has the best performance on nineteen of the twenty-five test problems. Furthermore, the performance of DE is only worse than ACOBC. For best solutions shown in Table 3, ACOBC provides the best results for twenty-one of the twenty-five test problems.

TSP problem: Traveling Salesman Problem (TSP) is a typical NP-complete problem. It is difficult to solve this problem using traditional methods. The TSP is not merely the traveling salesman problem. Many other NP problems can be attributed to TSP such as postman problem, nut production scheduling problem and product assembly line.

Therefore, the study of TSP is of great importance. The distance between each of n cities or their coordinates are provided. A traveling salesman starts to visit each city once and only once from certain city and finally returns to the starting city. The task involves how to arrange this traveling in order to make the shortest route. In short, TSP is to find a shortest trajectory among n cities or search for a city permutation $\pi(X) = \{V_1, V_2, ..., V_n\}$ in a natural subset $X = \{1, 2, ... , i , ... , n\}$.

Table 1: Benchmark functions

No.	Name	No.	Name
F01	Ackley	F14	Powel
F02	Alpine	F15	Rastrigin
F03	Brown	F16	Rosenbrock
F04	Dixon and Price	F17	Schwefel 2.26
F05	Fletcher-Powell	F18	Schwefel 1.2
F06	Griewank	F19	Schwefel 2.22
F07	Holzman 2 function	F20	Schwefel 2.21
F08	Levy 5	F21	Sphere
F09	Pathological function	F22	Step
F10	Penaltry #1	F23	Sum function
F11	Penaltry #2	F24	Zakharov
F12	Perm #1	F25	Wavy1
F13	Perm #2		

Table 2: ACOBC mean function values compared with other functions

No.	ABC	ACO	DE	ES	GA	HS	KH	ACOBC	PBIL	PSO
F01	3.03	3.07	2.93	3.48	3.25	3.53	1.09	1.00	3.61	3.09
F02	5.58	8.45	8.44	13.16	6.67	12.24	4.31	1.00	14.12	8.80
F03	5.11	8.8E3	1.00	56.01	2.27	37.49	4.10	7.73	11.53	19.45
F04	9.0E3	1.3E4	2.6E3	2.7E4	4.5E3	2.7E4	578.76	1.00	2.8E4	1.2E4
F05	1.24	3.45	1.53	3.65	1.62	3.05	1.44	1.00	2.93	2.71
F06	87.06	18.68	60.31	141.63	63.10	237.59	11.30	1.00	277.18	105.47
F07	1.4E4	1.8E4	7.6E3	5.6E4	8.0E3	5.3E4	1.0E3	1.00	6.7E4	2.2E4
F08	31.25	51.33	39.47	94.16	35.86	85.57	11.88	1.00	108.53	51.10
F09	2.75	2.69	2.02	1.00	2.22	3.19	3.05	3.03	2.87	2.44
F10	1.4E7	5.1E7	4.2E6	3.6E7	1.3E6	5.6E7	9.8E4	1.00	8.2E7	6.6E6
F11	3.2E6	5.8E6	1.4E6	8.4E6	1.3E6	1.4E7	6.7E4	1.00	1.8E7	2.6E6
F12	5.3E5	5.3E5	1.00	324.2	6.3E4	43.19	1.9E5	4.3E3	1.1E4	580.77
F13	9.3E3	1.7E4	1.00	164.42	1.6E4	280.03	1.7E16	1.8E3	1.5E4	111.04
F14	152.77	390	195.11	547.75	143.7	417.48	68.51	1.00	461.96	191.82
F15	1.46	2.67	2.21	2.91	2.30	2.75	1.39	1.00	2.92	2.25
F16	39.18	155.9	31.65	145.98	58.84	126.49	9.15	1.00	136.68	41.81
F17	1.84	1.27	2.32	2.58	1.00	3.07	2.01	1.69	3.10	3.14
F18	74.16	81.01	90.53	107.71	75.12	101.51	50.98	1.00	95.93	73.30
F19	1.00	1.85	1..14	2.48	1.39	2.05	1.11	1.30	2.01	2.28
F20	10.81	6.17	9.72	9.74	8.96	9.99	1.88	1.00	10.03	9.91
F21	149.54	235.5	77.15	354.59	186.1	332.20	14.27	1.00	350.98	141.94
F22	58.99	26.26	36.55	110.08	36.51	150.28	7.22	1.00	162.16	65.62
F23	178.18	272.8	84.44	413.53	109.8	414.22	24.22	1.00	474.86	144.0
F24	1.18	1.2E6	1.44	1.79	1.34	3.89	1.15	1.00	1.5	1.68
F25	1.52	1.05	1.59	2.65	1.47	2.76	1.2	1.00	3.07	2.03

ABC: Artificial bee colony, ACO: Ant colony optimization, DE: Differential evolution, ES: Evolutionary strategy, GA: Genetic algorithm, HS: Harmony search, PBIL: Probability based incremental learning, PSO: Particle swarm optimization

Table 3: ACOBC function values compared with other functions

No.	ABC	ACO	DE	ES	GA	HS	KH	ACOBC	PBIL	PSO
F01	3.68	3.75	3.70	4.44	4.13	4.58	1.19	1.00	4.72	4.00
F02	14.67	20.38	24.19	41.01	17.31	37.09	11.16	1.00	45.75	26.55
F03	4.86	1.00	1.48	40.37	2.64	24.32	2.51	4.75	9.81	16.43
F04	1.2E4	1.8E4	3.3E3	3.7E4	2.0E3	4.8E4	822.69	1.00	5.0E4	4.9E3
F05	1.41	5.34	2.36	5.61	1.84	4.97	2.36	1.00	5.41	4.32
F06	97.10	16.00	55.22	154.65	33.50	298.02	11.67	1.00	345.32	126.27
F07	3.3E4	4.6E4	2.6E4	2.2E5	1.4E4	2.1E5	2.9E3	1.00	2.4E5	2.3E4
F08	31.27	56.32	48.17	120.72	20.23	79.62	14.32	1.00	135.64	34.37
F09	3.36	3.27	2.42	1.00	2.47	3.83	3.77	3.74	3.61	2.69
F10	3.6E6	22.72	1.9E6	3.9E7	2.5E4	4.2E7	4.1E4	1.00	8.3E7	2.9E6
F11	2.8E7	1.00	1.6E7	8.0E7	5.3E6	2.0E8	6.7E5	16.67	2.7E8	3.4E7
F12	2.5E26	2.7E3	3.8E20	2.0E3	2.7E3	3.6E24	9.4E22	1.00	2.7E3	6.5E2
F13	1.3E15	4.6E2	3.0E8	8.5E1	4.6E2	1.2E1	1.1E12	1.00	4.6E17	3.8E12
F14	302.18	534.6	304.16	1.1E3	203.5	978.33	126.50	1.00	753.47	294.91
F15	2.13	3.88	3.24	4.13	3.43	4.46	1.99	1.00	4.35	3.38
F16	20.15	131.6	19.66	104.44	26.89	126.61	8.79	1.00	111.74	25.47
F17	2.26	1.32	2.84	3.36	1.00	3.99	2.36	1.22	3.89	4.10
F18	225.86	247.5	316.16	405.66	168.7	370.9	165.15	1.00	337.44	253.75
F19	1.94	4.11	2.27	5.26	2.37	4.49	2.12	1.00	4.10	3.06
F20	3.2E17	1.3E2	2.9E17	3.1E2	2.6E2	3.0E17	4.9E16	1.00	3.0E17	2.3E17
F21	240.29	499.2	173.61	711.64	228.6	692.17	25.38	1.00	706.85	270.53
F22	115.52	55.15	100.12	334.77	36.8	436.87	21.18	1.00	480.12	177.63
F23	164.87	222.6	70.18	397.63	82.56	407.32	19.74	1.00	476.94	123.63
F24	2.71	3.60	3.27	3.80	2.68	4.10	2.88	1.00	3.85	3.61
F25	1.55	1.00	1.84	2.70	1.46	3.13	1.15	1.00	3.56	1.85

ABC: Artificial bee colony, ACO: Ant colony optimization, DE: Differential evolution, ES: Evolutionary strategy, GA: Genetic algorithm, HS: Harmony search, PBIL: Probability based incremental learning, PSO: Particle swarm optimization

Here, i represents city number which must be integer number and its range varies from 1 to n. In other words, we minimize the total distance as represented in Eq. 9:

$$T_d = \sum_{i=1}^{n-1} d(V_i, V_{i+1}) + d(V_n, V_1) \tag{9}$$

where, $d(V_i, V_{i+1})$ is the distance between city V_i and city V_{i+1}.

Table 4: Solution for CTSP problem

Algorithm	Mean (10^4 km)	Best (10^4 km)	Worst (10^4 km)	SD (10^4 km)
ABC	3.89	2.49	3.15	1.52
ACO	2.2	2.06	3.15	0.27
DE	2.98	2.75	3.15	0.41
ES	2.27	2.14	3.15	0.41
GA	2.83	2.46	3.15	1.64
HS	3.24	2.93	3.30	0.94
KH	2.76	2.45	3.15	1.26
ACOBC	2.19	2.05	3.15	0.26
PBIL	2.75	2.33	3.15	1.36
PSO	3.12	2.86	3.26	1.11

ABC: Artificial bee colony, ACO: Ant colony optimization, DE: Differential evolution, ES: Evolutionary strategy, GA: Genetic algorithm, HS: Harmony search, PBIL: Probability based incremental learning, PSO: Particle swarm optimization

In this study, a particular kind of TSP, called Chinese TSP (CTSP) problem is considered. In CTSP, there are 31 main cities in China and the coordinates of each was given. In order to prove the ability of solving discrete problem, ACOBC is applied to solve the CTSP problem. In fact, the proposed method is used to find the shortest path among these cities. Firstly, the initial paths are randomly generated as follows:

31→8→23→12→11→24→27→6→16→10→30→25→26→17→4→15→14 →7→5→3→13→9→29→21→28→22→1→19→18→20→2→31

Its initial total distance is 41751 km.

As it is seen, ACOBC is efficiently capable of searching for much shorter path. The final path is shown as follows:

12→13→7→10→9→8→2→4→5→16→6→11→23→24→20→19→17→18→ 3→22→21→25→?26→28→27→30→29→31→1→15→14→12

The calculated distance is 16087 km. This is very close to the known shortest distance 15378 km. The results are obtained with population size and maximum generation number equal to 50 and 100, respectively.

Subsequently, ACOBC is compared with other methods discussed before for the CTSP problem. In order to get a fair comparison, all the methods are implemented in the same limited conditions, i.e., population size = 50 and generation number = 50. In order to remove the stochastic influence, 800 trials are conducted so as to get more accurate statistical results in Table 4.

From Table 4, it can be seen that for best and mean distance, ACOBC can find the shorter path as compared to the other methods under the same conditions. Considering the worst distance, all the methods can find the similar paths except HS and PSO. In addition, ACOBC has the smallest Standard Deviation (SD) value. That is to say, ACOBC can find the paths within smaller range.

Especially, ACOBC is superior to ACO that is known as one of the most efficient algorithm for the TSP problem. Based on the results, it can be concluded that ACOBC is well-suited for solving the TSP problem.

It is useful to discuss study results in comparison with other researches results that search in the same field of optimization. To summarize the comparison, ACOBC algorithm was superior due to the following reasons:

- No previous research discusses the main issue of this research, which is the 'obstacle case'
- Hybridizing ACO and ABC algorithms utilizes the optimum of both algorithms to reach best of the best and it also covers limitations in both algorithms
- The proposed algorithm ACOBC proves through calculations that it is superior to solve both, discrete and continuous data problems
- Founding of this research is compatible and supported with all previous researches as this was proved through previous discussion
- Founding of this research was compared with twenty one continuous data test problems and nine discrete data problems and found to be the best

CONCLUSION

In this study, a hybridization of the ACO and ABC methods, namely ACOBC, is proposed for the continuous and discrete optimization. Its main objective is to overcome ACO obstacle case limitations. The ACOBC integrates the capabilities of the ACO and the ABC to reach the optimal local and global solution. Moreover, a focused elitism scheme is applied to the method to further enhance its performance.

This research subject is very important as it touches many of human technical key problems, such as: network routing problem, travelling salesman problem and vehicle routing problem.

The results clearly demonstrate the superiority of ACOBC over ACO, ABC and other meta-heuristic algorithms. However, there are quite a few issues that merit further investigation such as analyzing the parameters used in the ACOBC method. The future study can focus on solving a more ubiquitous set of different continuous optimization and discrete problems. Finally, the study of CPU time used by the meta-heuristic approaches needs attention to make the proposed method more feasible for solving the practical engineering problems.

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