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A modified scout bee for artificial bee colony algorithm and its performance on optimization problems

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Abstract The artificial bee colony (ABC) is one of the swarm intelligence algorithms used to solve optimization problems which is inspired by the foraging behaviour of the honey bees. In this paper, artificial bee colony with the rate of change technique which models the behaviour of scout bee to improve the performance of the standard ABC in terms of exploration is introduced. The technique is called artificial bee colony rate of change (ABC-ROC) because the scout bee process depends on the rate of change on the performance graph, replace the parameter *limit*. The performance of ABC-ROC is analysed on a set of benchmark problems and also on the effect of the parameter *colony size*. Furthermore, the performance of ABC-ROC is compared with the state of the art algorithms.

1. Introduction

The ABC algorithm is introduced by Karaboga (2005), based on the foraging behaviour of a honey bees swarm. In ABC, the colony of artificial bees consists of three groups namely employed, onlooker and scout. A food source position represents a possible solution to the problem that is to be optimized and the nectar of a food source corresponds to the quality of the solution represented by the food source. During each cycle, the employed and onlooker bees are moving toward the food sources, thus calculating the nectar amounts and determining the scout bee and then moving them randomly onto the possible food sources. If the solution does not improve by a predetermined number of trials, the food source is abandoned. The number of trials for releasing a food source is equal to the value of *limit* which is an important control parameter of ABC (Karaboga and Gorkemli, 2014). After the *limit* is achieved, the employed bee is converted to a scout to search for new food sources.

The scout bee is an important component to control the exploration process (Karaboga and Basturk, 2008). However,

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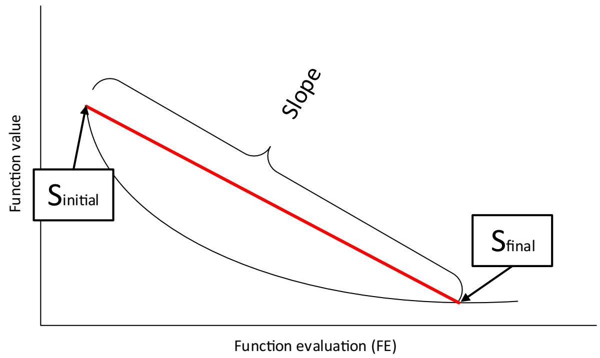


Figure 1 Illustration of slope in graph.

recent studies on ABC show that the scout bee component is redundant and sometimes does not present during the search process (Bullinaria and AlYahya, 2014a,b). As a result, the global exploration does not happen during the process because the global exploration is controlled by the scout bee component (Karaboga and Basturk, 2007). Therefore, we propose a new technique to control the scout bee process.

In this study, we propose a technique to replace the *limit* of the standard ABC algorithm. This technique is based on the changing of slope on the performance graph. The optimization process causes a decrease in the performance graph in case of function minimization and increasing of the performance graph in case of function maximization until the stopping condition achieved. By taking advantage of the changing pattern on the performance graph, we introduce a new technique called rate of change (ROC) to improve the performance of ABC in terms of exploration. The implementation of ROC technique in ABC algorithm is called artificial bee colony rate of change (ABC-ROC). Later, the ABC-ROC will be described in detail and its performance is tested on a set of test problems. The effect of newly added control parameters such as maxROC, maxTrace and maxFlag is investigated. The performance of ABC-ROC is also compared to the state of the art algorithms.

The rest of this paper is organized as follows. Section 2 discusses the literature review on ABC. Section 3 provides an overview of ABC algorithm. Section 4 describes the proposed, ABC-ROC algorithm. Section 5 gives a computational study and discussion, that include the explanation of the problems used in this experiment. Section 6 presents the experimental complexity of ABC and ABC-ROC algorithms. Section 7 presents the experiment on the effect of colony size (CS). Section 8 presents the comparisons of the number of scout bee between ABC and ABC-ROC. Finally, Section 9 concludes this paper and suggests the future direction.

2. Literature review

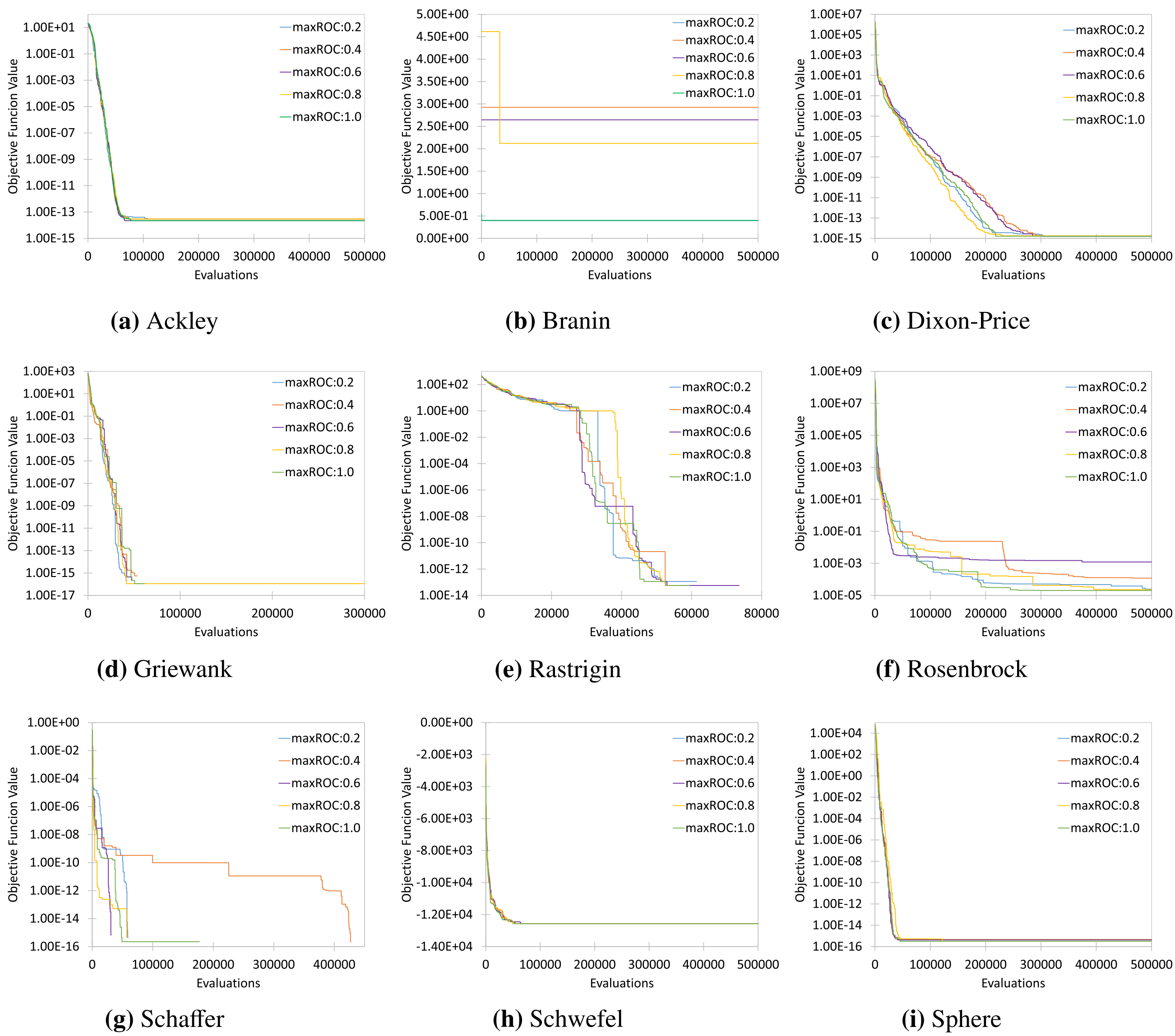
The standard ABC algorithm has successfully produced good results in the optimization problem because ABC has advantages of memory, local search and solution improvement mechanism (Basturk and Karaboga, 2006; Karaboga and Basturk, 2007, 2008; Zhao et al., 2010; Ozturk and Karaboga, 2011). However, in some cases, researchers found ABC may stuck in local optimum that affects the convergence performance and resulted in uncertainties on the results obtained from the standard ABC algorithm (Luo et al., 2013; Xiang and An, 2013; Kong et al., 2013).

Some researchers argued that the problem arose from the exploration process while other researchers believed that the problems are caused by the exploitation process of ABC. The exploration is the ability to investigate the various unknown region to discover the global optimum in solution space. This ability is performed by the scout bee component (Kong et al., 2013; Karaboga and Basturk, 2007). The exploitation is the ability to apply the knowledge of the previous good solutions to find better solutions. This process done by employed and onlooker bees (Kong et al., 2013; Karaboga and Basturk, 2007). In order to improve the exploration and exploitation process, many changes have been made on the standard ABC algorithm.

Aderhold et al. investigated the influence of the population size of the ABC and proposed two variants of ABC which use new methods for the position update of artificial bees (Aderhold et al., 2010). Stanarevic et al. proposed a modified ABC which includes "smart bee" that uses its historical memories of location and quality of the food source (Stanarevic et al., 2010). Lei et al, discovered that original ABC suffers from low precision and efficiency in solving optimization problems thus introduced a modification of the original ABC by adding an inertial weight which was inspired by particle swarm optimization (Lei et al., 2010).

Table 1 Test problems.

Test function	C	D	Interval	Min	Formulation
Ackley	MN	30	[−32,32]	$F_{min} = 0$	$f(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2}\right) - exp\left(\frac{1}{n}\sum_{i=1}^{n}cos(2\pi x_i)\right) + 20 + e$
Branin	MS	2	[−5,10] × [0,15]	$F_{min} = 0.398$	$f(x) = (x_2 - (5.1/4\pi^2)x_1^2 + (5/\pi)x_1 - 6)^2 + 10(1 - (1/8\pi))\cos(x_1) + 10$
Dixon-Price	UN	30	[−10,10]	$F_{min} = 0$	$f(x) = (1 - x_1)^2 + (1 - x_{10})^2 + \sum_{j=1}^{9}(x_j^2 - x_{j+1})^2$
Griewank	MN	30	[−600,600]	$F_{min} = 0$	$f(x) = \sum_{j=1}^{n}x_j^2/4000 - \prod_{j=1}^{n}\cos(x_j/\sqrt{j}) + 1$
Rastrigin	MS	30	[−5.12,5.12]	$F_{min} = 0$	$f(x) = x_1^2 + 2x_2^2 - 0.3\cos(3\pi x_1)$ $-0.4\cos(4\pi x_2) + 0.7$
Rosenbrock	UN	30	[−30,30]	$F_{min} = 0$	$f(x) = \sum_{j=1}^{n-1}(100(x_j^2 - x_{j+1})^2 + (x_j - 1)^2)$
Schaffer	MN	2	[−100,100]	$F_{min} = 0$	$f(x) = 0.5 + \frac{\sin^2(\sqrt{x^2+y^2}) - 0.5}{[1+0.001\cdot(x^2+y^2)]^2}$
Schwefel	MS	30	[−500,500]	$F_{min} = -12569.5$	$f(x) = \sum_{i=1}^{n}(-x_i\sin(\sqrt{\lvert x_i\rvert})) + \alpha\cdot n$
Sphere	US	30	[−100,100]	$F_{min} = 0$	$f(x) = \sum_{i=1}^{n}x_i^2$



(a) Ackley (b) Branin (c) Dixon-Price

(d) Griewank (e) Rastrigin (f) Rosenbrock

(g) Schaffer (h) Schwefel (i) Sphere

Figure 2 Convergence performance on various numerical functions for difference *maxROC* values.

Table 2 Parameters setting for ABC-ROC.

Related parameter	Test parameter		
	maxROC	maxTrace	maxFlag
maxROC	–	0.5	0.5
maxTrace	10	–	10
maxFlag	10	10	–

Lee and Cai proposed a new diversity strategy to balance the exploration and exploitation of ABC algorithm (Lee and Cai, 2011). Further, Zou et al. introduced a new variant of the ABC algorithm based on Von Neumann topology (VABC) and evaluated the performance on clustering problem (Zou et al., 2011). Stanarevic studied the new approach of mutation strategies of the standard ABC by implementing five different types of mutation strategies adapted from differential evolution algorithm in order to improve the exploitation performance of ABC (Stanarevic, 2011).

Akay and Karaboga proposed a modified ABC by controlling the frequency of perturbation to improve the convergence rate (Akay and Karaboga, 2012). Yan et al. proposed a hybrid ABC (HABC) by introducing the crossover operator of genetic algorithm (GA) to enhance the information exchange between bees (Yan et al., 2012). Moreover, Kashan et al introduced a new version of ABC called DisABC which was designed for binary optimization (Kashan et al., 2012).

Kong et al. proposed an improved ABC called IABC to balance the exploration and exploitation of the standard ABC by employing the orthogonal initialization method (Kong et al., 2013). Xiang et al. proposed an efficient and robust artificial bee colony (ERABC) by employing chaotic search on scout bee phase and combinatorial solution search equation to accelerate the search process (Xiang and An, 2013). Luo et al. implemented a modification on the onlookers bee of ABC and called the modified algorithm as convergence-onlookers ABC (COABC) in order to improve the exploitation (Luo et al., 2013).

Table 3 Comparisons of different setting of parameter maxROC.

Problem	Statistic	Parameter				
		maxROC:0.2	maxROC:0.4	maxROC:0.6	maxROC:0.8	maxROC:1.0
Ackley	Mean	3.52E−14	3.49E−14	3.51E−14	**3.45E−14**	3.53E−14
	SD	4.51E−15	3.92E−15	5.07E−15	**3.82E−15**	4.58E−15
	Best	2.93E−14	2.93E−14	**2.22E−14**	2.93E−14	2.22E−14
	Worst	4.35E−14	**4.00E−14**	4.35E−14	**4.00E−14**	**4.00E−14**
Branin	Mean	**3.98E−01**	7.57E+00	5.68E+00	5.72E+00	**3.98E−01**
	SD	**0.00E+00**	3.33E+00	2.15E+00	2.25E+00	**0.00E+00**
	Best	**3.98E−01**	2.92E+00	2.64E+00	2.12E+00	**3.98E−01**
	Worst	**3.98E−01**	1.40E+01	1.10E+01	1.10E+01	**3.98E−01**
Dixon	Mean	**2.65E−15**	2.94E−15	2.83E−15	2.85E−15	2.82E−15
	SD	**5.37E−16**	9.62E−16	5.80E−16	7.29E−16	5.58E−16
	Best	**1.55E−15**	1.66E−15	1.64E−15	1.78E−15	1.63E−15
	Worst	**3.64E−15**	6.96E−15	4.31E−15	5.00E−15	4.29E−15
Griewank	Mean	5.27E−12	2.47E−04	3.29E−04	**8.51E−17**	1.35E−04
	SD	2.89E−11	1.35E−03	1.80E−03	**1.04E−16**	7.39E−04
	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Worst	1.58E−10	7.40E−03	9.86E−03	**5.55E−16**	4.05E−03
Rosenbrock	Mean	9.50E−02	**5.70E−02**	1.66E−01	1.68E−01	1.39E−01
	SD	1.41E−01	**9.97E−02**	3.04E−01	3.02E−01	2.99E−01
	Best	2.46E−05	1.19E−04	1.22E−03	2.27E−05	**2.01E−05**
	Worst	5.74E−01	**4.14E−01**	1.23E+00	1.16E+00	1.55E+00
Schaffer	Mean	3.05E−05	1.90E−05	6.66E−06	**9.27E−07**	1.23E−05
	SD	8.71E−05	5.90E−05	2.54E−05	**4.80E−06**	6.74E−05
	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Worst	3.33E−04	2.79E−04	1.02E−04	**2.63E−05**	3.69E−04
Schwefel	Mean	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**
	SD	**1.85E−12**	**1.85E−12**	1.94E−12	**1.85E−12**	**1.85E−12**
	Best	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**
	Worst	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**
Sphere	Mean	5.20E−16	5.36E−16	5.51E−16	**5.18E−16**	5.34E−16
	SD	1.07E−16	**6.77E−17**	8.32E−17	7.83E−17	1.14E−16
	Best	3.19E−16	4.61E−16	4.22E−16	3.16E−16	**3.15E−16**
	Worst	**7.02E−16**	7.26E−16	7.21E−16	7.11E−16	7.66E−16

The best values are written in bold.

Karaboga and Gorkemli introduced a new version of ABC that model the behaviour of onlooker bee more accurately to improve the local search ability. The improvement is called quick ABC or qABC (Karaboga and Gorkemli, 2014). Hanbay and Talu proposed an improved artificial bee colony (I-ABC) to search for the optimal threshold value of synthetic aperture radar (SAR) image (Hanbay and Talu, 2014). Maeda and Tsuda presented a reduction of artificial bee colony algorithm which reduced the number of bees sequentially to reach a predetermined value (Maeda and Tsuda, 2015).

Kiran and Findik added a directional information to ABC algorithm for each design parameter in order to cope with the slow convergence performance of the standard ABC (Kran and Fndk, 2015). Ozturk et al. proposed a new solution generation mechanism for the discrete version of ABC using all similarity cases through the genetically inspired components (Ozturk et al., 2015).

In this paper, we consider to control the process of scout bee by introducing ROC technique. The ROC technique is considered the changing of slope on the performance graph. This technique is able to monitor the presence of local optimum on the graph itself. The proposed ROC technique is tested on numerical benchmark functions.

3. Artificial bee colony algorithm

The ABC model consists of three groups of bees which are employed, onlooker and scout that differ in terms of their functionality. Employed bee go to the food sources and come back to hive and exchange the information with onlooker bee by dancing on the dance area. Onlooker bee watches the dances and chooses the food sources depending on the dance moves. The employed bee which food sources have been abandoned becomes a scout and starts searching for a new food source.

For the purpose of optimization, the position of the 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 employed or onlooker is equal to the number of solutions in

Table 4 Comparisons of the ABC-ROC with state of the art algorithms.

Function	Cuckoo[a]		FA[a]		HS[a]		ABC[b]		qABC[b]		ABC-ROC[a]	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Ackley	1.71E+00	8.00E−01	8.25E+00	3.29E+00	1.24E−01	1.22E−02	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**
Branin	2.29E+00	2.53E+00	5.00E+00	4.19E−01	9.58E−01	3.38E−06	3.98E−01	**0.00E+00**	3.98E−01	9.70E−10	**3.56E+01**	**0.00E+00**
Dixon-Price	6.67E−01	5.65E−16	1.02E+03	2.16E+03	1.64E+00	7.62E−01	**0.00E+00**	**0.00E+00**	1.15E−12	3.36E−12	**0.00E+00**	**0.00E+00**
Griewank	4.84E−03	8.21E−03	6.98E+00	1.04E+01	1.62E−02	1.43E−02	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**
Rastrigin	8.42E+00	4.28E+00	6.30E+01	6.50E+01	1.87E+01	4.32E+00	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**
Rosenbrock	1.33E+00	1.91E+00	1.20E+05	2.56E+05	6.58E+01	3.33E+01	1.77E−01	2.66E−01	**1.33E−01**	**1.80E−01**	2.18E−01	3.13E−01
Schaffer	**0.00E+00**	**0.00E+00**	1.16E−02	1.85E−02	3.00E−14	4.48E−14	1.04E−10	4.83E−10	8.66E−06	7.83E−06	2.02E−05	6.77E−05
Schwefel	5.40E+02	3.49E+02	6.64E+03	1.63E+03	2.56E−03	3.21E−04	**−1.26E+04**	2.07E−12	**−1.26E+04**	2.51E−12	**−1.26E+04**	**1.85E−12**
Sphere	**0.00E+00**	**0.00E+00**	8.38E+02	1.40E+03	1.77E−02	2.44E−03	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**

The best values are written in bold.
[a] The results obtained from experiments.
[b] The results taken from Karaboga and Gorkemli (2014).

Table 5 Wilcoxon signed rank test results.

Function	Mean difference	*p*-Value
Ackley	−3.50E−14	0.004
Branin	−3.52E+01	0.000
Dixon-Price	−2.79E−15	0.023
Griewank	0.00E+00	–
Rastrigin	0.00E+00	–
Rosenbrock	−4.10E−02	0.072
Schaffer	−2.02E−05	0.010
Schwefel	0.00E+00	–
Sphere	−5.26E−16	0.000

the population. For the first step, the ABC generates a randomly distributed initial population $P(C = 0)$ of SN solutions (food source positions), where SN represents the size of employed or onlooker. Each solution $x_i (i = 1, 2, \ldots, SN)$ is a D-dimensional vector where D is the number of parameters to be optimized. The population of the positions (search process of the employed, onlooker and scout) is repeated until the maximum cycle number (MCN), $C = 1, 2, \ldots MCN$ is reached.

An employed bee produces a modification on the position using Eq. (1). If the nectar amount of the new position is higher than before, the bee memorizes the new position and discards the old one. Otherwise, the bee keeps the position of the previous in memory

$$v_{ij} = x_{ij} + \emptyset_{ij}(x_{ij} - x_{kj}), \tag{1}$$

where $k \in \{1, 2, \ldots, SN\}$ and $j \in \{1, 2, \ldots, D\}$ are randomly chosen indexes; k is determined randomly and should differ from i, and $\emptyset_{ij}$ is a randomly generated number between [−1,1].

After all employed bees complete the search process, the sharing information begins where the food sources and their position information are shared with the onlooker bee. An onlooker bee evaluates the nectar information and chooses a food source with a probability, p_i, related to its nectar amount following Eq. (2):

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

where fit_i is the fitness value of the solution i and SN is the number of food sources. The employed bee produces a modification of the position and checks the nectar amount of the candidate source. If the nectar is higher than the previous one, the onlooker bee memorizes the new position and discards the old one.

The food source of which the nectar is abandoned by the bees is replaced with a new food source by the scouts by Eq. (3) in case the position cannot be improved further. The parameter "limit" is the control parameter to determine the abandonment of the food sources within the predetermined number of cycles

$$x_i^j = x_{min}^j + rand(0,1)(x_{max}^j - x_{min}^j). \tag{3}$$

The main steps of ABC are given as below (Karaboga, 2005):

Step 1: Initialize the population of solutions $x_i, \; i = 1 \ldots SN$
Step 2: Evaluate the population
Step 3: cycle = 1

Table 6 Time complexities of the ABC and ABC-ROC algorithms on Rosenbrock function.

D	T_0	T_1	$\widehat{T}_2$ of ABC	$\widehat{T}_2$ of ABC-ROC	Complexity of ABC ($(\widehat{T}_2 - T_1)/T_0$)	Complexity of ABC-ROC ($(\widehat{T}_2 - T_1)/T_0$)
10	0.1701	2.4439	19.4663	19.2039	100.0913	98.5484
30	0.1701	4.7524	19.7964	19.5204	88.4583	86.8351
50	0.1701	7.0030	20.3086	20.0246	78.2362	76.5662

Step 4: Repeat
Step 5: Produce new solution v_i for the employed bees by using Eq. (1) and evaluate them
Step 6: Apply greedy selection process. If the solution does not improve, increase the trial counter.
Step 7: Calculate the probability values p_i for the solutions x_i by Eq. (2)
Step 8: Produce the new solutions $v_i$for the onlookers from the solutions
Step 9: x_i selected depending on p_i and evaluate them
Step 10: Apply greedy selection process. If the solution does not improve, increase the trial counter.
Step 11: Determine the abandoned solution for the scout, if exist (trial $\geqslant$ limit), and replace it with a new randomly produce solution x_i by Eq. (3)
Step 12: Memorize the best solution achieved so far
Step 13: cycle = cycle + 1
Step 14: until cycle = MCN

Based on the procedure of ABC, the scout bee will be executed if the "trial" exceeded the "limit". The "trial" counter will increase if the solution does not improve and will be reset to zero if the solution is improved during the process of employed and onlooker bees. The employed and onlooker bees will produce local solutions. The local solutions usually will improve but not necessary become the best solution. The best solution is the global solution which will be selected after the employed, onlooker and scout bee process (for example in Step 12). For certain problems such as studied by Bullinaria and AlYahya (2014b), the local solutions are constantly improved, resulting the trial is always reset to zero. Thus, the trial counter does not exceed the limit causing the global exploration by scout bee is difficult to occur. For this reason, an improved scout bee process is proposed. The proposed artificial bee colony rate of change (ABC-ROC) will consider global solution instead of local solution by using slope on graph as reference. The next section will discuss the proposed ABC-ROC.

4. The proposed artificial bee colony rate of change (ABC-ROC)

The scout bee is important to control the exploration process. The scout bee component is controlled by *limit* in original ABC. However, if the *limit* does not achieve, the scout bee is not involved in the process. We introduce another technique to control the scout bee process. By taking advantage of the slope on the performance graph, we calculate the slope and keep track the function value. In other words, the process is basically keeping track the rate of change of the performance graph. Thus, we called our proposed technique as rate of change (ROC) technique. Implementation of ROC in ABC algorithm is called artificial bee colony rate of change (ABC-ROC).

In ABC-ROC, we add three new parameters called *maxTrace*, *maxROC*, and *maxFlag*. The *maxTrace* value decides the starting point to calculate the slope. In other words, *maxTrace* can be viewed as the straight line on the graph. The *maxROC* value gives a maximum value of the slope to be considered before calling scout bee. The *flag* value is to keep track when the graph does not improve or $slope = 0$.

During the first cycle, the initial function value, $S_{initial}$, is stored in a memory. A counter, (called *trace*) increases by one during each cycle. When *trace* is equal to "maxTrace", the final function value is stored as S_{final} and *trace* are reset to zero. Then, the slope is calculated using Eq. (4)

$$|slope| = \frac{\delta y}{\delta x} = \frac{(S_{final} - S_{initial})}{S_{initial}}. \tag{4}$$

Based on Eq. (4), in order to calculate slope, an initial point and a final point are needed. The $S_{initial}$ is referred as an initial point because the initial function value is always higher (in case of function minimization). Once the "maxTrace" is achieved, the final point, S_{final} is stored. Fig. 1 illustrates the example of slope in graph.

The advantage of using slope is that it can determine the situation when the solution does not improve (in case of stagnation or stuck in local optimum) directly from the graph. The pseudo-code of the proposed ABC-ROC is given below:

Step 1: Set parameters (MCN,SN,*maxROC*,*maxTrace*, *maxFlag*)
Step 2: Initialize the population of solutions $x_i,\ i = 1, 2, \ldots, SN$
Step 3: Evaluate the population
Step 4: cycle = 1; counter = 1; flag = 0;
Step 5: repeat
Step 6: Produce new solution v_i for the employed bees using Eq. (1) and evaluate them
Step 7: Apply the greedy selection process for the employed bees
Step 8: Calculate the probability values P_i for the solutions x_i using Eq. (2)
Step 9: Produce the new solutions v_i for the onlookers from the solutions x_i selected depending on P_i and evaluate them
Step 10: Apply the greedy selection process for the onlookers
Step 11: if trace = = *maxTrace*
Step 12: Calculate slope using Eq. (4)
if slope = = 0
  Scout bee produce new random solution x_i using Eq. (3)
  flag = flag + 1
  maxTrace = *maxTrace*∗2
else if slope $\leqslant$ *maxROC* AND slope != 0
  Scout bee produce new random solution x_i using Eq. (3)
  maxROC = slope

else slope = = $maxROC$
  trace = 0
Step 13: if flag = = $maxFlag$
  Scout bee produces new random solution x_i using Eq. (3)
  reset $maxROC$ to initial $maxROC$
  reset $maxTrace$ to initial $maxTrace$
  flag = 0
Step 14: Memorize the best solution achieved
Step 15: cycle = cycle + 1
Step 16: trace = trace + 1
Step 17: until cycle = MCN

Based on the pseudo-code of ABC-ROC, we set three decision rules to decide the process of scout bee based on the slope's characters. The decision rules are set as below:

Rule 1: $slope == 0$
Rule 2: $slope \leqslant maxROC\ AND\ slope! = 0$
Rule 3: $flag == maxFlag$

The slope is calculated after trace is equal to $maxTrace$. If the trace is equal to $maxTrace$, then the slope is calculated using Eq. (4). If the slope is equal to zero (solution does not improve), then the first rule will be considered where the scout bee begins searching for a new solution, the *flag* is incremented by one and the $maxTrace$ is doubled (the length of the line is increasing). The increment of $maxTrace$ is important to ensure the slope always there because the slope heavily depends on the $maxTrace$.

Next, if the slope is less than or equal to $maxROC$ and the slope is not zero, then the second rule is applied. In this rule, the scout bee begins searching for a new solution, and the $maxROC$ is set to the current slope. This process is important to control the presence of the scout bee. If the $maxROC$ is not set to new value, then the scout bee process always happens and the exploitation will be disrupted.

Finally, if none of the rules applied, the scout bee process does not occur and $maxROC$ is set to the current slope. After that, the flag value needs to be checked. If the flag is equal to *maxFlag*, then the third rule is applied, where the scout bee begins searching for a new solution, the $maxROC$ and $maxTrace$ are reset to the initial value, and the flag is reset to zero. In the event that the solution is not improving, the increment of flag until *maxFlag* will help to find other new solutions. All the parameters need to be reset to the initial value because we consider that if this rule is applied, the food sources found by the scout bee is a new solution that should be reassessed. This process will assist the algorithm to escape the local minima at the end of the cycle.

By using slope, we can track the improvement of the result globally instead of using "limit" which track the improvement locally. In addition, we can add a decision rules from the slope's characters, thus provide more opportunities for scout bee to contribute during the search process.

5. Computational study and discussion

The experiments is conducted to test the parameters $maxROC$, $maxTrace$ and $maxFlag$ with different values. The effect of these parameters is analysed by means of the convergence performance and the quality of the solutions obtained from this algorithm.

Further, the ABC-ROC is compared with different state of art algorithms, including firefly algorithm (FA) (Yang, 2008), cuckoo search (Cuckoo) (Yang and Deb, 2009) and harmony search algorithm (HS) (Geem et al., 2001). The FA and Cuckoo are natural phenomenon algorithm, inspired by the flashing behaviour of fireflies whilst the Cuckoo mimic the parasitism behaviour of cuckoo bird laying egg (Yang, 2008; Yang and Deb, 2009). Comparison with FA and Cuckoo which represent the natural phenomenon algorithm as well as the development of both algorithm is after the introduction of ABC

Table 7 Effect of the colony size (CS) on the performance of ABC-ROC.

CS	Ackley		Branin		Dixon-Price		Griewank		Rastrigin	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
4	1.47E+01	4.63E+00	7.02E+00	6.11E+00	2.75E+05	3.44E+05	1.04E+02	7.12E+01	8.84E+01	3.83E+01
6	8.44E+00	4.29E+00	9.53E+00	3.24E+00	5.69E+03	2.03E+04	7.13E+00	1.37E+01	2.44E+01	1.58E+01
12	1.14E−01	3.53E−01	8.87E+00	2.58E+00	2.32E−06	7.63E−06	1.57E−02	1.81E−02	6.30E−01	8.46E−01
24	3.91E−14	**3.19E−15**	**2.97E+00**	2.24E+00	5.30E−15	9.41E−15	2.87E−03	5.64E−03	**0.00E+00**	**0.00E+00**
50	3.55E−14	4.47E−15	7.70E+00	2.51E+00	**2.72E−15**	**6.68E−16**	1.39E−03	4.56E−03	**0.00E+00**	**0.00E+00**
100	3.27E−14	3.30E−15	5.04E+00	**1.65E−16**	2.78E−15	1.20E−15	4.07E−17	5.44E−17	**0.00E+00**	**0.00E+00**
200	**3.05E−14**	3.28E−15	6.92E+00	1.24E+00	4.27E−10	3.66E−10	**1.48E−17**	**3.84E−17**	**0.00E+00**	**0.00E+00**

CS	Rosenbrock		Schaffer		Schwefel		Sphere	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
4	3.11E+07	2.52E+07	2.42E−01	2.11E−01	-9.52E+03	1.05E+03	1.21E+04	6.11E+03
6	7.02E+05	2.64E+06	3.32E−02	6.32E−02	**−1.13E+04**	4.89E+02	4.07E+02	8.10E+02
12	2.71E+00	3.40E+00	6.36E−04	1.44E−03	−1.23E+04	1.92E+02	6.95E−16	1.20E−16
24	5.80E−01	1.17E+00	1.48E−04	3.69E−04	−1.26E+04	4.09E+01	5.62E−16	1.00E−16
50	2.49E−01	6.02E−01	3.40E−06	1.49E−05	−1.26E+04	**1.85E−12**	5.28E−16	8.55E−17
100	3.93E−02	8.40E−02	**8.77E−08**	**4.80E−07**	−1.26E+04	**1.85E−12**	4.76E−16	8.63E−17
200	**1.72E−02**	**5.18E−02**	2.03E−06	1.11E−05	−1.26E+04	**1.85E−12**	**4.46E−16**	**7.68E−17**

The best values are written in bold.

Table 8 Comparison between the number of scout bee of ABC and ABC-ROC.

Function	ABC		ABC-ROC
	Limit = CS^*D	Limit = $(CS^*D)/2$	
Ackley	150	125	24
Branin	834	522	34
Dixon-Price	25	20	24
Griewank	151	76	27
Rastrigin	162	143	11
Rosenbrock	19	8	24
Schaffer	321	121	21
Schwefel	143	122	33
Sphere	250	200	24

CS is colony size and *D* is dimension.

algorithm. For HS algorithm, the comparison is done because HS is developed using different approaches which mimic the artificial phenomenon of musical harmony (Geem et al., 2001). In addition, the comparison is also been done with ABC and quick ABC (qABC) and the results is taken from Karaboga and Gorkemli (2014).

For a fair comparison, the same parameters setting and maximum number of evaluation are used, following (Karaboga and Akay, 2009; Karaboga and Gorkemli, 2014). The colony size is 50 and the maximum number of evaluation is 500 000. The "Limit" for ABC and qABC is set to $(CS * D)/2$ as suggested by Karaboga and Gorkemli (2014).

The Wilcoxon statistical test is carried out on ABC-ROC algorithms to validate the results. The well-known benchmark numerical problems with different characters are considered in order to test the performance of ABC-ROC. The test problems consists of several characters (C), dimensions of the problems (D), the bounds of the search spaces and the global optimum values. The test problems are presented in Table 1 with C categorized as unimodal-seperable (US), unimodal-nonseperable (UN), multimodel-seperable (MS) and multimodel-nonseperable (MN).

Fig. 2 shows the convergence performance of ABC-ROC with difference *maxROC* values.

Next, the experiment is conducted to test the performance of individual parameter. The parameters setting is shown in Table 2. This table should be read in the form of a column. For example, to test the *maxROC* parameter, both parameters *maxTrace* and *maxFlag* should be set to 10 respectively. The results are presented according to the test function.

Table 3 shows the mean and standard deviation (SD) for test problems with different setting of parameter *maxROC*. Moreover, the best and worst objective function values are presented in this table.

For all parameter settings of *maxROC*, the ABC-ROC hits optimum value for Rastrigin problem for each of 30 independent runs. Table 3 presents the results for parameter *maxROC*. For Ackley function, ABC-ROC gives the best mean, SD and worst values for *maxROC:0.8* and the best values for the column "Best" is given by *maxROC:0.6* and *maxROC:1.0*. For Branin function the best value for mean, SD and Best are produced by *maxROC:0.2* and *maxROC:1.0* whereas the best value for column "Worst" are given by *maxROC:0.6* and *maxROC:0.8*. For Dixon-Price function the best mean, SD, best and worst values are produced by *maxROC:0.2*. The best results of column "Best" are given for all parameters with all settings for Griewank function. For this function, the best mean, SD and worst are given by *maxROC:0.8*. For Rosenbrock function the best mean, SD and worst are produces by *maxROC:0.4* whereas *maxROC:1.0* given the best for column "Best".

For Schaffer function *maxROC:0.8* produced the best Mean, SD, best and worst. For Schwefel function all parameter maxROC produced best results in terms of mean, SD, best and worst of 30 independent runs for this function. For Sphere function, the best mean and best are given by *maxROC:0.8* whereas the best SD given by *maxROC:0.4* and the best for column "Worst" is given by *maxROC:0.2*.

The experiment has been done to evaluate the effect of parameter *maxROC* of ABC-ROC algorithm. For certain problems, ABC-ROC produced less different results even with the different setting of parameter. Further, the results for parameter *maxTrace* and *maxFlag* are provided in Tables A.9 and B.10 respectively in Appendix.

In comparison of ABC-ROC with the state of art algorithms (Cuckoo, FA, HS, ABC and qABC), the results are presented in Table 4. The parameters setting for Cuckoo and FA are based on (Yang, 2014) and for ABC and qABC are following (Karaboga and Gorkemli, 2014). For ABC-ROC, the parameters are set with *maxROC:0.5*, *maxTrace:100* and *maxFlag:50* by using trial and error approach. From the table, the mean of 30 independent runs and the standard deviations are presented for considered problems. For a fair comparison, the table values below E-12 are accepted as 0 as in Karaboga and Akay (2009) and Karaboga and Gorkemli (2014).

The best performance of Schaffer function is produced by Cuckoo, where it successfully hits the optimum value. HS produces average performance for all functions and Cuckoo produces average performance for all functions except Schaffer and Sphere. Focusing on ABC-ROC, the best performance for mean is given by Branin function. For Schwefel function, the result produced is the same as ABC and qABC but ABC-ROC produces more consistent results based on the lowest SD value. The result of ABC-ROC on Griewank and Rastrigin function showed similar results with ABC and qABC.

Results on Table 4 clearly show that ABC, qABC and ABC-ROC algorithms outperform Cuckoo, FA and HS on the considered test problems. The results also indicate that ABC-ROC outperforms ABC and qABC for certain problems. However, it is not very clear that there is a significant difference between the performances of the ABC and ABC-ROC which produced similar results for several problems. Hence, in order to validate the performance of ABC and ABC-ROC, the Wilcoxon signed rank test was used in this paper.

The Wilcoxon test is a nonparametric statistical test to analyse the behaviour of evolutionary algorithms and suitable for use in small sample size (Garća et al., 2009; Kulluk et al., 2012). The test results are shown in Table 5. The first column represents the test functions. The Second column gives the mean difference between the results of the ABC and qABC and the last column gives the p value that is an important determiner of the test. Since the mean difference column value is 0 for Griewank, Rastrigin and Schwefel functions, there are six test problems that can be discussed. Among them, the p value is different from Rosenbrock is higher that significance

Table A.9 Comparisons of different setting of parameter maxTrace.

Problem	Statistic	Parameter				
		maxTrace:20	maxTrace:40	maxTrace:60	maxTrace:80	maxTrace:100
Ackley	Mean	3.56E−14	3.56E−14	**3.48E−14**	3.50E−14	3.50E−14
	SD	4.14E−15	**4.03E−15**	4.25E−15	4.34E−15	4.13E−15
	Best	2.93E−14	2.93E−14	2.93E−14	**2.58E−14**	**2.58E−14**
	Worst	4.35E−14	**4.00E−14**	4.35E−14	**4.00E−14**	**4.00E−14**
Branin	Mean	8.14E+00	2.69E+00	5.32E+00	**3.98E−01**	5.56E+01
	SD	3.77E+00	1.98E+00	2.54E+00	**0.00E+00**	2.89E−14
	Best	3.53E+00	4.67E−01	2.61E+00	**3.98E−01**	5.56E+01
	Worst	1.94E+01	7.78E+00	1.10E+01	**3.98E−01**	5.56E+01
Dixon	Mean	2.78E−15	2.74E−15	2.92E−15	**2.68E−15**	2.81E−15
	SD	4.87E−16	5.57E−16	8.08E−16	**4.30E−16**	5.46E−16
	Best	2.09E−15	1.44E−15	**1.44E−15**	1.62E−15	1.64E−15
	Worst	4.27E−15	3.60E−15	5.20E−15	**3.60E−15**	4.09E−15
Griewank	Mean	**2.47E−04**	1.07E−03	2.47E−04	4.11E−04	4.93E−04
	SD	1.35E−03	4.17E−03	**1.35E−03**	2.25E−03	1.88E−03
	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Worst	**7.40E−03**	1.97E−02	**7.40E−03**	1.23E−02	7.40E−03
Rosenbrock	Mean	1.46E−01	**5.84E−02**	9.48E−02	2.22E−01	8.49E−02
	SD	1.82E−01	**8.35E−02**	1.42E−01	4.93E−01	1.34E−01
	Best	9.84E−04	**4.51E−05**	1.29E−04	3.12E−04	2.75E−04
	Worst	6.88E−01	**3.66E−01**	4.86E−01	2.50E+00	5.92E−01
Schaffer	Mean	3.04E−05	5.74E−06	5.18E−06	**3.68E−12**	1.20E−06
	SD	1.19E−04	2.04E−05	2.84E−05	**1.01E−11**	6.57E−06
	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Worst	6.29E−04	8.25E−05	1.56E−04	**5.01E−11**	3.60E−05
Schwefel	Mean	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**
	SD	**1.85E−12**	**1.85E−12**	**1.85E−12**	**1.85E−12**	**1.85E−12**
	Best	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**
	Worst	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**
Sixhump	Mean	**−1.03E+00**	**−1.03E+00**	**−1.03E+00**	**−1.03E+00**	**−1.03E+00**
	SD	**4.16E−16**	**4.16E−16**	4.40E−16	4.29E−16	4.29E−16
	Best	**−1.03E+00**	**−1.03E+00**	**−1.03E+00**	**−1.03E+00**	**−1.03E+00**
	Worst	**−1.03E+00**	**−1.03E+00**	**−1.03E+00**	**−1.03E+00**	**−1.03E+00**
Sphere	Mean	**5.10E−16**	5.30E−16	5.23E−16	5.20E−16	5.19E−16
	SD	**8.35E−17**	8.48E−17	9.15E−17	1.03E−16	8.67E−17
	Best	**2.76E−16**	3.27E−16	3.20E−16	2.98E−16	3.17E−16
	Worst	7.13E−16	7.36E−16	7.22E−16	**7.02E−16**	7.16E−16

The best values are written in bold.

level 0.05 which mean this function is not enough evidence to reject the null hypothesis (0.072 > 0.05). These tests show that in these conditions, the performance of ABC-ROC algorithm is significantly better than ABC for another five test functions (Ackley, Branin, Dixon-Price, Schaffer and Sphere). These tests are based on the final results obtained by the algorithms.

Generally, we could interpret the simulation and test results as when the three rules are used for scout to search for a new solution, the convergence performance of ABC is significantly improved in early and late cycles. The effect of parameter *maxTrace* causes the algorithm to escape local optimum in early cycles and the parameter *maxFlag* may cause the algorithm to escape the local optimum during the end of cycles. Hence, a good tuning of the parameters promises much more flexible profile for scout bee and can generate superior convergence performance for ABC-ROC algorithm.

6. Time complexity of ABC algorithms

In this section, a time complexity analysis is carried out for ABC and ABC-ROC on Rosenbrock function. The complexities are calculated for dimensions 10, 30 and 50 as been suggested by Suganthan et al. (2005) and Karaboga and Gorkemli (2014). The results are shown in Table 6 for ABC and ABC-ROC algorithms. This experiment was performed using Windows 7 Professional (SP2) on Intel(R) Core(TM) i7 920 2.67 GHz processor with 6GB RAM and the algorithms were coded by using MATHLAB2014a.

The code execution time for this system was obtained and demonstrated in Table 6 as T_0. Next, the computing time for Rosenbrock function for 200,000 function evaluations is presented as T_1 in the table. Each algorithm was run for 5 times for 200,000 function evaluations and the average computing

Table B.10 Comparisons of different setting of parameter maxFlag.

Problem	Statistic	Parameter				
		maxFlag:20	maxFlag:40	maxFlag:60	maxFlag:80	maxFlag:100
Ackley	Mean	**3.44E−14**	3.62E−14	3.58E−14	**3.44E−14**	3.51E−14
	SD	**3.58E−15**	4.27E−15	4.38E−15	3.81E−15	3.90E−15
	Best	**2.93E−14**	**2.93E−14**	**2.93E−14**	**2.93E−14**	**2.93E−14**
	Worst	**4.00E−14**	4.35E−14	4.35E−14	4.35E−14	**4.00E−14**
Branin	Mean	5.52E+00	5.56E+01	8.51E+00	**3.98E−01**	3.56E+01
	SD	1.87E+00	2.89E−14	2.28E+00	**0.00E+00**	7.23E−15
	Best	2.73E+00	5.56E+01	6.00E+00	**3.98E−01**	3.56E+01
	Worst	1.10E+01	5.56E+01	1.72E+01	**3.98E−01**	3.56E+01
Dixon	Mean	2.78E−15	2.82E−15	2.80E−15	2.74E−15	**2.71E−15**
	SD	6.99E−16	6.01E−16	**5.86E−16**	6.38E−16	5.98E−16
	Best	**9.67E−16**	2.08E−15	1.59E−15	1.44E−15	1.83E−15
	Worst	4.07E−15	4.30E−15	4.09E−15	4.54E−15	**3.87E−15**
Griewank	Mean	2.47E−04	2.47E−04	1.09E−15	4.98E−04	**9.62E−17**
	SD	1.35E−03	1.35E−03	5.52E−15	2.72E−03	**1.23E−16**
	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Worst	7.40E−03	7.40E−03	3.03E−14	1.49E−02	**5.55E−16**
Rosenbrock	Mean	2.24E−01	**1.12E−01**	1.65E−01	1.76E−01	1.45E−01
	SD	3.46E−01	**2.39E−01**	3.23E−01	2.55E−01	2.51E−01
	Best	8.14E−04	**5.41E−05**	1.72E−04	2.77E−04	6.71E−05
	Worst	1.50E+00	1.16E+00	1.53E+00	**9.65E−01**	1.22E+00
Schaffer	Mean	3.29E−05	2.20E−05	3.80E−06	4.08E−06	**2.02E−06**
	SD	1.19E−04	8.14E−05	1.44E−05	1.69E−05	**1.04E−05**
	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Worst	6.29E−04	4.35E−04	5.81E−05	8.69E−05	**5.72E−05**
Schwefel	Mean	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**
	SD	**1.85E−12**	**1.85E−12**	**1.85E−12**	**1.85E−12**	**1.85E−12**
	Best	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**
	Worst	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**	**−1.26E+04**
Sixhump	Mean	**−1.03E+00**	**−1.03E+00**	**−1.03E+00**	**−1.03E+00**	**−1.03E+00**
	SD	4.23E−16	**4.10E−16**	4.40E−16	4.29E−16	4.34E−16
	Best	**−1.03E+00**	**−1.03E+00**	**−1.03E+00**	**−1.03E+00**	**−1.03E+00**
	Worst	**−1.03E+00**	**−1.03E+00**	**−1.03E+00**	**−1.03E+00**	**−1.03E+00**
Sphere	Mean	**5.12E−16**	5.38E−16	5.47E−16	5.42E−16	5.37E−16
	SD	8.30E−17	**7.47E−17**	1.01E−16	1.01E−16	9.06E−17
	Best	**2.76E−16**	4.07E−16	3.20E−16	3.03E−16	3.25E−16
	Worst	**7.13E−16**	7.29E−16	7.38E−16	7.44E−16	7.44E−16

The best values are written in bold.

time of the algorithms are presented as $\widehat{T}_2$. The algorithm complexities were calculated by $(\widehat{T}_2 - T_1)/T_0$.

From Table 6, the time complexity of ABC-ROC is slightly lower than ABC since the contribution of scout bee causes the number of function evaluations to increase. In addition, the increment rate of ABC-ROC for every dimension is lower than ABC. So, it can be concluded that there is not a strict dependence between the dimension of the functions and the complexities of ABC-ROC and ABC.

7. Experiment on colony size (CS)

For experiments in this section, the parameters are set same as the previous experiments with the maximum evaluation number = 500,000. The ABC-ROC was tested on the test problems for several colony size: 4, 6, 12, 24, 50, 100 and 200. The results of this experiment are presented in Table 7.

The best value is written in Bold. Based on Table 7, the ABC-ROC performs worst when CS is small (CS < 12) except for Schwefel function where the best objective values are produced when CS = 6. For other functions, the good results are obtained by using much larger CS (CS > 12). For Rastrigin function, ABC-ROC hits optimum value when using larger CS (CS > 12). In addition, the results indicate that the ABC-ROC produces best value when CS = 200 for most functions (Ackley, Griewank, Rosenbrock and Sphere).

8. Comparison of the number of scout bee

This section discusses the different between parameter “limit” of the standard ABC algorithm and maxROC of ABC-ROC algorithm. Table 8 shows the number of scout bees for ABC and ABC-ROC. “Limit” for ABC is set to $CS * D$ and $(CS * D)/2$ is suggested by Karaboga and Basturk (2008) and Karaboga and Gorkemli (2014), respectively. For ABC-ROC, maxROC is set to 0.8, maxTrace is to 60 and maxFlag is to 100.

Based on Table 8, the number of scout bees of ABC-ROC is less than ABC. However, the results from Table 11 indicate that ABC-ROC is capable to produce results better than or similar to those of ABC algorithm. This indicates that the ABC-ROC has reduced the usage of scout bee but able to produced better results.

9. Conclusion

This paper presents a new definition of the scout bee process, replacing the parameter limit of the standard ABC. The algorithm is called ABC-ROC, that keeps track the changing of the slope on the performance graph. Experimental studies indicate that the new definition significantly improves the convergence performance of the ABC when the parameters *maxROC*, *maxTrace* and *maxFlag* are set appropriately. These additional parameters give more flexible approach and make the scout bee to be more presence during the search process.

The performance of the ABC-ROC is compared with that of the standard ABC and other state of the art algorithms. The results indicate that the ABC-ROC produces promising results for considered problems. Moreover, the effect of colony size and the complexity is carried out. The ABC-ROC can be considered as an alternative approach for optimization problems. In the future, the performance of ABC-ROC can be tested with more complex problem such as classification, clustering and neural network.

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Appendix A. Comparisons of different setting of parameter maxTrace

See Table A.9.

Appendix B. Comparisons of different setting of parameter maxFlag

See Table B.10.

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