Artificial bee colony algorithm: a survey

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Abstract: In recent years, swarm intelligence has proven its importance for the solution of those problems that cannot be easily dealt with classical mathematical techniques. The foraging behaviour of honey bees produces an intelligent social behaviour and falls in the category of swarm intelligence. Artificial bee colony (ABC) algorithm is a simulation of honey bee foraging behaviour, established by Karaboga in 2005. Since its inception, a lot of research has been carried out to make ABC more efficient and to apply it on different types of problems. This paper presents a review on ABC developments, applications, comparative performance and future research perspectives.

Keywords: artificial bee colony algorithm; ABCA; warm intelligence; meta-heuristics; evolution strategy.

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1 Introduction

Many natural phenomena following collective behaviour of individuals, inspire researchers to develop population-based optimisation algorithms. These population-based optimisation algorithms work on fitness evaluation and therefore the population of potential solutions is expected to move towards the better fitness areas of the search space. Population-based optimisation algorithms find near-optimal solutions to the difficult optimisation problems through motivation from nature. Evolution (Fogel, 2000) and swarm intelligence-based algorithms (Eberhart et al., 2001) are two important types of population-based algorithms. Genetic algorithm (GA) (Holland, 1975), genetic programming (GP) (Koza, 1990), evolutionary strategy (ES) (Rechenberg, 1998) and evolutionary programming (EP) (Fogel et al., 1966) are popular evolutionary algorithms (EAs). One of the EAs which has been introduced recently is differential evolution (DE) algorithm (Qin et al., 2009; Rogalsky et al., 2000; Omran et al., 2005; Das et al., 2009; Storn and Price, 1995; Price, 1996; Price et al., 2005). In recent years, swarm intelligence has also attracted the interest of many research scientists of related fields. Bonabeau et al. (1999) has defined the swarm intelligence as “any attempt to design algorithms or distributed problem-solving devices inspired by the collective behaviour of social insect colonies and other animal societies”. Bonabeau et al. (1999) focused their study on social insects only, e.g., termites, bees, wasps and different ant species. Swarm intelligence is emerged from collaborative, trial and error behaviour of social insects. In Swarm intelligence, members of swarm are considered to be interactive, active, dynamic and with very small inherent intelligence. Researchers have analysed such behaviours and designed algorithms that can be used to solve numerical optimisation problems in many science and engineering domains. Previous research (Yagmahan and Yenisey, 2008; Kennedy and Eberhart, 1995; Price et al., 2005; Vesterstrom and Thomsen, 2004) has shown that algorithms based on swarm intelligence have great potential in the field of numerical optimisation. The algorithms that have emerged in recent years include (ACO) (Dorigo et al., 1999), particle swarm optimisation (PSO) (Kennedy and Eberhart, 1995), bacteria foraging optimisation (BFO) (Passino, 2002). Exploration and exploitation are two important concerns for designing a robust search process. While exploration process is related to the independent search for an optimal solution, exploitation uses existing knowledge to bias the search. The artificial bee colony algorithm (ABCA) introduced by Karaboga (2005) is one approach that has been used to find an optimal solution for numerical optimisation problems. This algorithm is inspired by the behaviour of honey bees when seeking a quality food source. ABC scheme is relatively a simple, fast and population-based stochastic search technique.

Recently, ABC research attracted a lot of researchers from different parts of the world. Only in the year 2011, 80 publications are reported on ABC as per scopus record. Different Researchers are exploring application areas of engineering, science and medical with ABC. This paper presents a survey report on ABC developments, applications, and comparative performance. Further, a discussion is presented to encounter the future research perspectives of ABC.

2 Behaviour of honey bee in nature

ABCA is inspired from the foraging behaviour of honey bees. One of the swarms exists in nature is honey bee swarm which follows collective intelligent manner, while searching the food. The honey bee swarm has many qualities like bees can communicate the information, can memorise the environment, can store and share the information and take decisions based on that. According to changes in the environment, the swarm updates itself, assigns the tasks dynamically and moves further by social learning and teaching. This intelligent behaviour of bees, motivates researchers to simulate above foraging behaviour of the bee swarm. The behaviour of real honey bees can be summarised in the heads namely, food sources, employed bees, unemployed bees, foraging behaviour, and dances.

2.1 Food sources

While searching the food, bee selects a particular flower (called food source) for herself. From this food source bee collects the information about, the amount of nectar that food source contains, how easily this nectar can be extracted from the flower, how far and in which direction it is from the nest. Bee stores these facts as a single quantity (termed as total profitability for this particular food source) for the sake of convenience and simplicity.

2.2 Employed bees

The available food sources are exploited by particular group of bees. These bees are called employed bees and each of these keeps the profitability (i.e., richness, distance and direction from the hive) of associated food source.

2.3 Unemployed bees

Employed bees share their information with another group of bees (called unemployed bees) with a certain probability. Unemployed bees are responsible to summarise the information which they get from employed bees and to select a food source to exploit. These unemployed bees are further divided into two categories as onlooker bees and scouts bees. The Onlooker bees are the bees which collect the information from the employed bees in the hive and after analysing data, they establish a food source for themselves whereas the Scouts bees are responsible for finding the new food sources around the hive. When some of the existing food sources exhaust then these bees start searching the environment around the hive and find the new food sources randomly. In a honey bee swarm, usually on an average 50% bees are employed, 50% bees are unemployed and 5% to 10% of the total bees are scouts.

2.4 Foraging behaviour

The most important characteristic of the honey bee swarm is foraging behaviour. In foraging process, bee leaves the hive and starts searching the food. When she gets a food source, she extracts the nectar from it and stores it in her stomach. She extracts the nectar till 30–120 minutes according to conditions like richness, distance of food source from hive. Then with the secretion of enzymes in her stomach, honey making process starts and she unloads nectar in empty cells after reaching to the hive. Finally she shares her information with other bees in the hive in form of various types of dance, defined in the next section.

2.5 Dance

In order to tell other bees residing in the hive that how plentiful her food source is, how far and in which direction it is from the hive, employed bee performs particular type of steps called dance, on the different parts of hive area. Von Frisch (1967) (the 1973 Nobel Prize winner) decoded the dance language of bees. He noted that the direction information of a bee dance indicates the location of a food source relative to the sun and the distance of the food source are signaled by different kinds of dances. Tarpy (2009) and Wenner and Wells (1990) argued that floral odors on a foragers body are the primary cues that enabled the employed bees to locate new food sources. Either dance languages or floral odors indicate that there is communication among bees that fulfill foraging behaviour. By means of dance, she wants to inform others that whether they should follow or not follow her food source to extract. Her dance movements are done on different areas of hive so that more bees can be informed about food source associated with her. When she does dancing, the other bees touch her with their antenna in order to taste the nectar of her food source. Based on the profitability of food source, employed bee performs one of the following dance forms,

1 Round dance: This type of dance does not inform about the direction of food source, but bee does this dance when food source is near (not more than about 100 metres far) to hive.

2 Waggle dance: This dance form informs the other bees about the direction of food source with respect to the sun light and employed bees select this dance form if source is far from the hive. Speed of dance is proportional to the distance of food source from the hive.

3 Tremble dance: If a bee has taken a longer time to unload the nectar then she starts trembling and indicates that she does not know about current profitability of her food source as she took a lot of time before informing others.

3 Artificial bee colony algorithm

Swarm-based optimisation algorithms find solution through collaborative trial and error method. Peer to peer learning behaviour of social colonies is the main driving force behind the development of many efficient swarm-based optimisation algorithms. ABC optimisation algorithm is a recent addition in this category. Like any other population-based optimisation algorithm, ABC consists of a population of potential solutions. With reference to ABC, the potential solutions are food sources of honey bees. The fitness is determined in terms of the quality (nectar amount) of the food source. There are three types of bees in the colony: onlooker bees, employed bees and scout bee. Number of employed bees or onlooker bees are equal to the food sources. Employed bees are associated with food sources while onlooker bees are those bees that stay in the hive and use the information gathered from employed bees to decide the food source. One of the employed bees, whose food source is exhausted, becomes scout bee and she searches the new food source randomly.

Similar to the other swarm-based algorithms, ABC is an iterative process. There are two fundamental processes which derive the evolution of an ABC population: the variation process, which enables exploring different areas of the search space and the selection process, which ensures the exploitation of the previous experiences. However it has been shown that ABC may occasionally stop proceeding toward the global optimum even though the population has not converged to a local optimum (Karaboga and Akay, 2009). ABC process requires cycle of four phases: initialisation phase, employed bees phase, onlooker bees phase and scout bee phase, each of which is explained below:

3.1 Initialisation of the population

Initially, ABC generates a uniformly distributed population of SN solutions where each solution $x_i (i = 1, 2, ..., SN)$ is a D-dimensional vector. Here D is the number of variables in the optimisation problem and x_i represents the i^{th} food source in the population. Each food source is generated as follows:

$$x_i^j = x_{min}^j + rand(0, 1)(x_{max}^j - x_{min}^j), \forall j = 1, 2, ..., D \tag{1}$$

where x_{min}^j and x_{max}^j are bounds of x_i in j^{th} direction.

3.2 Employed bees phase

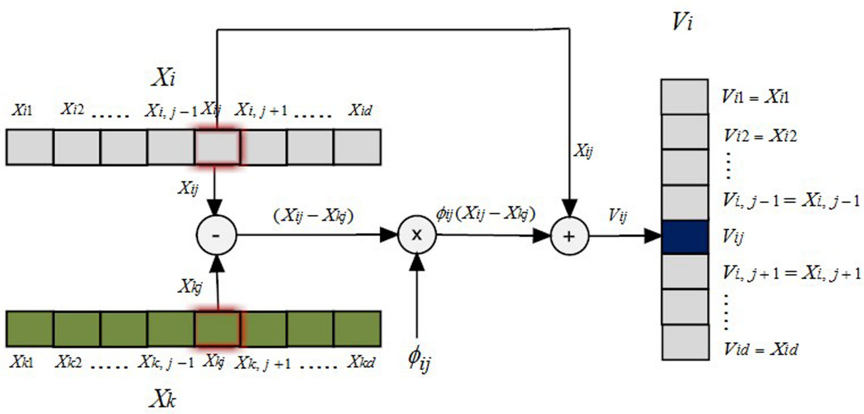
In this phase, employed bees modify the current solution based on the information of individual experiences and the fitness value (nectar amount) of the new solution . If the fitness value of the new food source is higher than that of the old food source, the bee updates her position with the new one and discards the old one. The position update equation for j^{th} dimension of i^{th} candidate in this phase is shown in following equation:

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \tag{2}$$

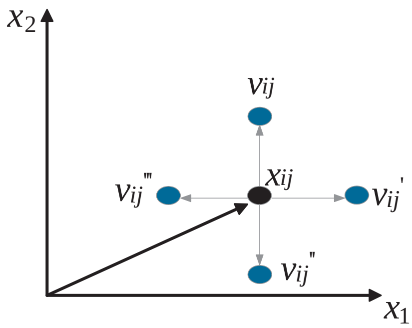
where $\phi_{ij}(x_{ij} - x_{kj})$ is called step size, $k \in \{1, 2, ..., SN\}$, $j \in \{1, 2, ..., D\}$ are two randomly chosen indices. k must be different from i so that step size has some significant contribution and ϕ_{ij} is a random number between [–1, 1].

Position update process in employed bee phase is shown in Figure 1(a). Here x_i represents the current position of a bee and highlighted box represents the randomly choosen direction j. x_k is the randomly choosen bee. In this step the direction j of a random bee $k \neq i$ is subtracted from same direction of i^{th} bee then this difference is multiplied by a random number $\phi_{ij} \in [-1, 1]$. Finally this quantity is added to j^{th} dimension of x_i to get j^{th} dimension of new food position v_{ij}. This v_{ij} is represented by vertical vector in the figure whose all other dimensions are same as of x_i and is generated in the neighbourhood of x_i. If we consider only $2-D$ search space then possible positions for this new food source v_{ij} can be seen in Figure 1(b).

Figure 1 (a) Illustrating a simple position update equation execution (b) Different possible new vectors formed in neighbourhood of x_{ij} due to position update equation in 2-D search space (see online version for colours)



(a)



(b)

3.3 Onlooker bees phase

After completion of the employed bees phase, the onlooker bees phase is started. In this phase, all the employed bees share the fitness information (nectar) of the upated solutions (food sources) and their position information with the onlooker bees in the hive. Onlooker bees analyse the available information and select a solution with a probability, p_i, related to its fitness. The probability p_i may be calculated using following expression (there may be some other but must be a function of fitness):

$$p_i = \frac{fit_i}{\sum_{i=1}^{SN} fit_i} \tag{3}$$

where fit_i is the fitness value of the i^{th} solution . As in the case of the employed bee, onlooker bee produces a modification in the position in her memory and checks the fitness of the candidate source. If the fitness is higher than that of the previous one, the bee memorises the new position and forgets the old one.

3.4 Scout bees phase

If the position of a food source is not updated for a predetermined number of cycles, then the food source is assumed to be abandoned and scout bees phase is started. In this phase the bee associated with the abandoned food source becomes scout bee and the food source is replaced by the randomly chosen food source within the search space. In ABC, the predetermined number of cycles is a crucial control parameter which is called *limit* for abandonment. Assume that the abandoned source is x_i then the scout bee replaces this food source with new x_i as follows:

$$x_i^j = x_{min}^j + rand[0,1](x_{max}^j - x_{min}^j), \forall j = 1, 2, ..., D \tag{4}$$

where x_{min}^j and x_{max}^j are bounds of x_i in j^{th} direction.

3.5 Main steps of the ABCA

Mainly in the ABCA, the exploitation process is carried out by onlookers and employed bees and exploration process is carried out by scout bees in the search space. The pseudo-code of the ABCA is shown in Algorithm 1 (Karaboga and Akay, 2009):

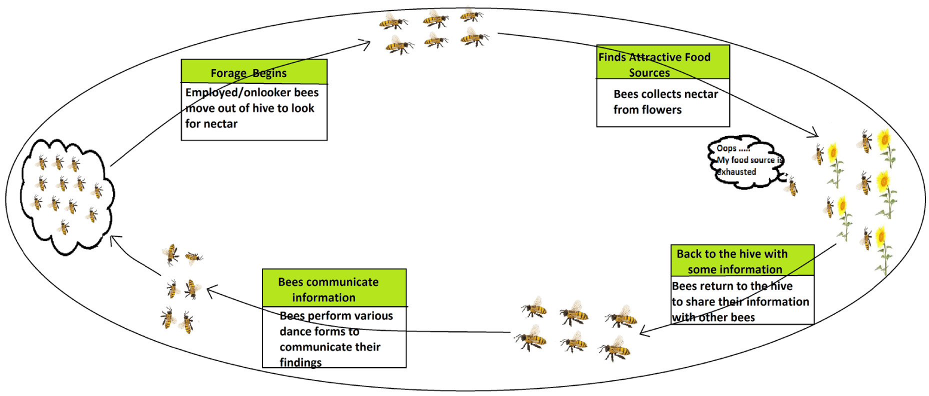
Algorithm 1 artificial bee colony algorithm

Initialise the population of solutions, $x_i (i = 1, 2, ..., SN)$ using (1);
cycle = 1;
while cycle $<=$ MCN **do**
1. Produce new solution v_i for the employed bees using (2) and evaluate them
2. Apply the greedy selection process for the employed bees
3. Calculate the probability values p_i for the solutions x_i using (3).
4. Produce the new solutions v_i for the onlookers for the selected solutions x_i depending on p_i and evaluate them
5. Apply the greedy selection process for the onlookers
6. Determine the abandoned solution for the scout, if exists, and replace it with a new randomly produced solution x_i using (4)
7. Memorise the best solution achieved so far
8. cycle = cycle + 1

end while

Figure 2 shows the simulated foraging behaviour of the bees in ABC. It is clear from Figure 2 that in each phase only half of the bees forage the food sources and communicate the gathered information to the other bees which remains in the hive by performing various dances. The bee whose food source is exhausted, becomes scout bee and searches new solution randomly.

Figure 2 Social behaviour of honey bees (see online version for colours)



3.6 *Control parameters of ABC*

There are three main control parameters of the ABC algorithm: Number of food sources, *limit* and ϕ_{ij} (a uniformly distributed random number in the range [–1, 1]). As stated by Karaboga (2005) and Akay and Karaboga (2012b), ABC performance is very sensitive to the choice of ϕ_{ij} and *limit*. Some settings of control parameters are suggested by Karaboga (2005):

- $\phi_{ij} = rand[-1, 1]$ (A uniformly distributed random number in the range $[-1, 1]$)
- $limit$ should be $(\frac{colonysize}{2}) \times D$
- $colonysize$ should be $50 - 100$ bees.

One more parameter play an important role in ABC, which is the probability p_i generated for probabilistic selection using some probability calculation methods. This probabilistic selection is a function of fitness values of the current population members. In basic ABC, roulette wheel selection approach is applied. The slices of roulette wheel are propotional to the size of fitnesses.

In ABC, ϕ_{ij} is the weight to the difference between current food source and randomly selected food source. This parameter is responsible to maintain the proper diversity mechanism of the search procedure in ABC, usually it is a uniformly distributed random number in the range [–1, 1].

limit is another important parameter in ABCA which is responsible to explore new areas of search space. After employed and onlooker bees phases it is checked whether there is any food source which is exhausted (in other words, whether there is any candidate's solution who is not modifying its position for a particular number of iterations called 'limit'). If exhausted food source exists, then it is abandoned and replaced with a new food source discovered by the scout. This process in ABC, mimics the negative feedback mechanism and fluctuation property of self organisation. In ABC, in each iteration only one food source can be exhausted, i.e., only one bee can be scout bee. Colony of ABC consists of employed bees, onlooker bees and scout bees, in which number of onlooker bees is equal to the number of employed bees and scout bee is one of the employed bees whose food source is exhausted. From literature it can be concluded that as the colony size increases, the algorithm produces better results. However, after a sufficient value for colony size, any increment in the value does not improve the performance of the ABCA significantly. Karaboga and Basturk (2008) carried out some experimental results for the different test problems, and suggested that colony size of 50 - 100 can provide an acceptable convergence.

Research in the field of ABC has given a lot of attention in the recent years. Next section reviews the ABC research.

4 ABC modifications

Since the inception of ABC, a lot of research has been carried out to make ABC efficient, widely applicable and to apply ABC on different types of problems. In order to get rid of the drawbacks of basic ABC, researchers have improved ABC in many ways. The potentials, where ABC have been improved, may be broadly classified into following four categories:

1 introducing new strategies in ABC and fine tuning of existing control parameters

2 introducing new control parameters in ABC

3 hybridisation of ABC with other population-based probabilistic or deterministic algorithms

4 miscellaneous.

For each of the above mentioned category, brief reviews are given in the following subsection.

4.1 Introducing new strategies in ABC and fine tuning of existing control parameters

Control parameters play a significant role for any stochastic optimisation algorithm. These parameters directly affect the performance of algorithm so in order to get desirable results under the time constraint, values of these parameters must be fine tuned. Karaboga (2005) observed that the value of ϕ_{ij} in the range of [–1, 1] is a good initial choice. The value of *limit* should be $SN \times D$, where, SN is the total number of potentials and D is the dimension of the problem. Karaboga and Basturk (2008) suggested that colony size of 50–100 can provide an acceptable convergence.

Haijun and Qingxian (2008) proposed a new strategy for the initialisation scheme in ABC, by making the initial group symmetrical, and the Boltzmann selection mechanism was employed instead of roulette wheel selection for improving the convergence ability of the ABCA.

In order to maximise the exploitation capacity of the onlooker stage, Tsai et al. (2009) proposed interactive artificial bee colony (IABC). In IABC, the Newtonian law of universal gravitation in the onlooker phase was introduced in which onlookers are selected based on a roulette wheel.

To modify ABC behaviour for constrained search space, Mezura-Montes and Cetina-Domínguez (2012) proposed four modifications related with the selection mechanism, the scout bee operator, and the equality and boundary constraints. Instead of fitness proportional selection, tournament selection is performed to exploit employed bee food sources by onlooker bees. Second, they employed dynamic tolerance for equality constraints by rewriting equality constraint as inequality constraint, where a tolerance ϵ, which slightly extends the region of the search space for corresponding constraint, is defined as:

$$\epsilon(t+1) = \frac{\epsilon(t)}{dec} \tag{5}$$

where t is the iteration counter and dec is the decreasing rate value of each iteration ($dec > 1$) such that it starts with large feasible region and by iteration it reduces. Third, a smart flight operator is used in scout bee phase, according to which an abandoned food source is not randomly initialised in search space but it is generated with the help of the food source to be replaced x_{ij}, which is utilised as a base to create a search direction defined by the best solution y in the current population and a randomly chosen solution x_k as following:

$$v_{ij} = x_{ij} + \phi_{ij}(x_{kj} - x_{ij}) + (1 - \phi_{ij})(y_j - x_{ij}) \tag{6}$$

And forth modification was employed for boundary constraint handling. If any solution is generated outside the range, it is set between the upper and lower limit of that variable of the problem as:

$$v_{ij} = \begin{cases} 2 * x_{min} - v_{ij}, & \text{if } v_{ij} < x_{min}, \\ 2 * x_{max} - v_{ij}, & \text{if } v_{ij} > x_{max}, \\ v_{ij}, & \text{otherwise} . \end{cases} \tag{7}$$

In 2011, for solving constrained optimisation problems, Karaboga and Akay (2011a) modified the probability calculation method for onlooker bees. After all employed bees complete the search process, they share the nectar information of the food sources and their position information with the onlooker bees on the dance area by calculating probability values. Since infeasible solutions are allowed to populate in the colony, a modification is needed here to assign probability values for infeasible solutions as well as for feasible ones. They used the following assignment of calculating probability for onlooker bees:

$$p_i = \begin{cases} 0.5 + \left(\frac{fitness_i}{\sum_{i=1}^{SN} fitness_i}\right) \times 0.5, & \text{if solution is feasible,} \\ \left(1 - \frac{violation_i}{\sum_{i=1}^{SN} violation_i}\right) \times 0.5, & \text{if solution is infeasible.} \end{cases} \tag{8}$$

where $violation_i$ is the penalty value of the solution x_i and $fitness_i$ is the fitness value of the solution x_i, which is proportional to the nectar amount of that food source. Probability values of infeasible solutions are between 0 and 0.5 while those of feasible ones are between 0.5 and 1. By a selection mechanism like roulette wheel, solutions are selected probabilistically proportional to their fitness values in case of feasible solutions and inversely proportional to their violation values in case of infeasible solutions. In order to evaluate the performance of the modified ABCA, they used a set of 13 benchmark and it is concluded that modified ABCA can be efficiently used for solving constrained optimisation problems.

Pan et al. (2011) introduced a discrete artificial bee colony (DABC) algorithm and its application in lot-streaming flow shop scheduling problem. To guarantee an initial population with certain quality and diversity, a portion of food sources are generated by using some priority rules (explained in Pan et al., 2011) whereas the rest are produced randomly. In DABC, both employed and onlooker bees apply a self-adaptive strategy to find neighbouring food sources. In self-adaptive strategy, at the beginning, an initial neighbour list (NL) with a specified length is generated by filling the list one by one randomly with existing neighbouring approach. Then the DABC algorithm works in the way that initially one approach from the NL is taken out and used to generate a new food source for an employed bee or onlooker. If the new food source successfully replaces the current one, this approach will enter into a winning neighbouring list (WNL). Once the NL is empty, it is refilled with 75% from the WNL list and 25% is refilled by a random selection from existing approaches. If the WNL is empty (because of performance of search near an optimum with negligible population diversity), the latest NL is used again. This process is repeated until a termination criterion is reached. As a result, the proper neighbouring approach can be gradually learned by the algorithm itself to suit to the particular problem and the particular phase of search process.

Gao and Liu (2011) proposed an improved solution search equation in ABC, which is based on the fact that the bee searches only around the best solution of the previous iteration to improve the exploitation. They proposed two major changes in the basic ABC. The first change is the following novel initialisation approach which employs opposition-based learning method and chaotic systems with sinusoidal iterator to generate initial population.

$$x_{ij} = x_{minj} + ch_{kj}(x_{maxj} - x_{minj}) \tag{9}$$

where $ch_{k+1} = sin(\pi ch_k), ch_k \in (0, 1)$ and k is the iteration counter. The mapped variables in equation (9) can distribute in search space with ergodicity, randomness and irregularity.

Getting inspiration from the DE variant $DE/best/1$, the following solution search equation is developed as a second modification in the ABC. The proposed strategy ABC/best/1 can drive the new candidate solution only around the best solution of the previous iteration. Therefore, the proposed solution search equation described by equation (10) can increase the exploitation of ABC.

$$ABC/best/1 : v_{ij} = x_{bestj} + \phi_{ij}(x_{r_1 j} - x_{r_2 j}) \tag{10}$$

where the indices r_1 and r_2 are mutually exclusive integers randomly chosen from the set $\{1, 2, ..., SN\}$, and different from the base index i; X_{best} is the best individual vector with the best fitness in the current population and $j \in \{1, 2, ..., D\}$ is randomly chosen indices; ϕ_{ij} is a random number in the range [–1, 1].

Coelho and Alotto (2011) introduced a Gaussian ABCA approach and applied it to Loney's Solenoid problem. In the proposed algorithm, authors applied the Gaussian distribution to produce candidate food positions instead of uniform distribution, in both the employed bee and onlooker bee phases. In order to improve the performance of the algorithm, following novel alternative was proposed.

$$x_{ij}^{new} = \begin{cases} x_{ij}^{old} + \phi_{ij}(x_{ij} - x_{kj})\beta\alpha, & \text{if } r_1 > p, \\ x_{ij}^{old} + \phi_{ij}(x_{ij} - x_{kj})2\alpha, & \text{if } r_1 \leq p. \end{cases} \tag{11}$$

where $r_1 \in [0, 1]$ is random number extracted from a uniform distribution, $p \in [0.1, 1]$ is a parameter whose value influences the numerical results and

$$\beta = |s|, \alpha = 0.5 - 0.25\frac{iter}{maxiter} \tag{12}$$

where s is a set of random numbers extracted from a Gaussian (normal) distribution and *iter* and *maxiter* indicate the current iteration and the maximum iteration number, respectively. Practically, p is responsible for the balance between Gaussian and uniform distribution and the search radius decreases automatically as iteration proceeds.

Zhu and Kwong (2010) proposed an improved ABCA called gbest-guided artificial bee colony (GABC) algorithm by incorporating the information of global best (gbest) solution into the solution search equation to improve the exploitation. GABC is inspired by PSO (Kennedy and Eberhart, 1995), which, in order to improve the exploitation, takes advantage of the information of the global best (gbest) solution to guide the search by candidate solutions. They modified the solution search equation of ABC as follows:

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) + \psi_{ij}(y_j - x_{ij}) \tag{13}$$

where the third term in the right-hand side of equation (13) is a new added term called gbest term, y_j is the j^{th} element of the global best solution, ψ_{ij} is a uniform random number in $[0, C]$, where C is a non-negative constant. According to equation (13), the gbest term can drive the new candidate solution towards the global best solution, therefore, the modified solution search equation described by (13) can increase the exploitation of ABCA. Note that the parameter C in (13) plays an important role in balancing the exploration and exploitation of the candidate solution search. Sharma et al. (2012) modify the structure of the swarm and proposed a variant of ABC namely group social learning in ABC.

4.2 Introducing new control parameters in ABC

The basic version of the ABCA is very efficient for multimodal and multidimensional basic functions. However, the convergence rate of the algorithm is poorer when working with constrained problems, composite functions and some non-separable functions (Karaboga and Akay, 2009). In order to improve the convergence rate, Akay and Karaboga (2012b) analysed the effects of the perturbation rate that controls the frequency of parameter change, the scaling factor (step size) that determines the magnitude of change in parameters while producing a neighbouring solution, and the parameter 'limit' on the performance of the ABCA and proposed a modified version for solving efficiently real-parameter optimisation problems. One of the modifications in the ABCA is made in the perturbation process to control the frequency of perturbation. In the basic version of ABC, this frequency is fixed as, while producing a new solution v_i, changing only one parameter of the parent solution x_i results in a slow convergence rate. But in the proposed ABCA, a new control parameter, modification rate (MR) was introduced. For each x_{ij}, a uniformly distributed random number, $(0 \leq R_{ij} \leq 1)$, is produced and if the random number is less than MR, then the parameter x_{ij} is modified through the equation (14)

$$v_{ij} = \begin{cases} x_{ij} + \phi_{ij}(x_{ij} - x_{kj}), & \text{if } R_{ij} < MR, \\ x_{ij} \text{ otherwise.} \end{cases} \tag{14}$$

where $k \in \{1, 2, ..., SN\}$ is randomly chosen index that has to be different from i and MR is the modification rate which takes value between 0 and 1. A lower value of MR may cause solutions to improve slowly while a higher one may cause higher diversity in a solution and hence in the population. Further a ratio of the variance operator also modified. In the basic ABC, a random perturbation, which avoids getting stuck at local minima, is added to the current solution in order to produce a new solution. This random perturbation is the difference of the solutions (x_i and x_k) weighted by a random real number ϕ_{ij}. This ϕ_{ij} varies in the range [–1, 1] in the basic ABC, while in the modified ABCA, it varies within the range $[-SF, SF]$; Hence, magnitude of the perturbation is controlled by a control parameter called the scaling factor (SF). A lower value of SF allows the search to fine tune the process in small steps while causing slow convergence. A larger value of SF speeds up the search, but it reduces the exploitation capability of the perturbation process. Automatic tuning of SF is conducted by Rechenberg's 1/5 mutation rule which states that the ratio of successful mutations to all mutations should be 1/5 (Back, 1996).

ABC with better exploration capabilities, some times having problem of exploitation and convergence speed. For these inefficiencies, Li et al. (2012) proposed an improved ABCA called I-ABC, in which, the best-so-far solution, inertia weight and acceleration coefficients were introduced to modify the search process. In I-ABC, the neighbourhood solution v_{ij} is calculated as:

$$v_{ij} = x_{ij} \times w_{ij} + 2(\phi_{ij} - 0.5)(x_{ij} - x_{kj})\Phi_1 + \psi_{ij}(y_j - x_{kj})\Phi_2 \tag{15}$$

where w_{ij} is the inertia weight which controls impact of the previous solution x_{ij}, y_j is the j^{th} dimension of the best-so-far solution, ϕ_{ij} and ψ_{ij} are random numbers between $[0, 1]$, Φ_1 and Φ_2 are positive parameters that could control the maximum step size. Inertia weight w_{ij} and acceleration coefficients Φ_1 and Φ_2 are defined as functions of the fitness in the search process of ABC. In equation (15), w_{ij} and Φ_1 are set equal as:

$$w_{ij} = \Phi_1 = \frac{1}{(1 + exp(-fit_i/ap))} \tag{16}$$

and to maintain balance between exploration and exploitation, the Φ_2 is set 1 in employed bee phase and in onlooker bee phase it is set as Φ_1,

$$\Phi_2 = \frac{1}{(1 + exp(-fit_i/ap))} \tag{17}$$

They also proposed a new strategy called prediction and selection in artificial bee colony (PS-ABC), in which the neighbourhood solution v_{ij} is calculated by three strategies; according to equation (2) in original ABC, according to equation (15) in I-ABC and according to equation (13) in GABC, which is prediction phase of algorithm and then in selection phase it adopts that solution which has better fitness among these three and previous solution.

4.3 Hybridisation of ABC with other population-based probabilistic or deterministic algorithms

Baykasoglu et al. (2007) incorporated the ABCA with shift neighbourhood searches and greedy randomised adaptive search heuristic and applied it to the generalised assignment problem. Kang et al. (2009b) combined Nelder-Mead simplex method with ABCA.

Wu et al. (2012) proposed improvement of global swarm optimisation (GSO) by hybridising it with ABC and PSO. They used neighbourhood solution generation scheme of ABC and accepted new solution only when it was better than previous one to improve GSO performance. Lien and Cheng (2012) hybridised ABC and PSO algorithms and proposed particle-bee algorithm (PBA) for construction site layout optimisation. Yan et al. (2012) proposed a hybrid artificial bee colony (HABC) algorithm by introducing the crossover operator of GA to ABC in information exchange (social learning) phase between bees for data clustering. Further, Shanthi and Amalraj (2012) combined ABC with Harmonic search algorithm called collaborative artificial bee colony algorithm (C-ABC) for adapting the connection weights, network architecture, the features of time series input data and the learning algorithms according to the problem environment.

Suguna and Thanushkodi (2011) proposed an independent rough set approach hybrid with ABCA for dimensionality reduction. In the proposed work, effects of the perturbation rate, the scaling factor (step size), and the *limit* were investigated on real-parameter optimisation. Zhang et al. (2011b) hybridised ABC with forward neural network (FNN). Further, Horng (2011) incorporated multilevel maximum entropy thresholding (MET) with ABC. Gao et al. (2011) combined ABC with DE. An eliminative rule and the new search strategy is introduced into the iteration of ABC to improve the convergence rate. Then, to maintain the population diversity, DE simulates evolution and all individuals are taken into account in each generation. Li et al. (2011c) proposed a hybrid algorithm combining an external Pareto archive set and ABC. To balance the exploration and exploitation capability of the algorithm, the scout bees in the hybrid algorithm are divided into two parts. The scout bees in one part perform randomly search in the predefined region while each scout bee in another part randomly select one non-dominated solution from the Pareto archive set. Kang et al. (2011) combined Rosenbrock's rotational direction method with ABC for accurate numerical optimisation. There are two alternative phases of Rosenbrock ABC: the exploration phase realised by ABC and the exploitation phase completed by the rotational direction method. Tasgetiren et al. (2011) hybridised a DABC with a variant of iterated greedy algorithm to find the permutation that gives the smallest total flow-time. Iterated greedy algorithms are comprised of local search procedures based on insertion and swap neighbourhood structures. Zhang et al. (2011a) proposed new algorithm called hybrid multi-objective artificial bee colony (HMOABC), which is based on ABC, summation of normalised objective values and diversified selection (SNOVDS) and non-dominated sorting genetic algorithm II (NSGA-II) approach, to solve multi-objective model for burdening optimisation of copper strips production.

Dereli and Das (2011) proposed a hybrid bee(s) algorithm for solving container loading problems. In the proposed algorithm, a bee(s) algorithm was hybridised with the heuristic filling procedure for the solution of container loading problems. Further, Huang and Lin (2011) proposed a new bee colony optimisation algorithm with idle-time-based filtering scheme and its application for open shop-scheduling problems. They categorised the foraging behaviours of bees in two terms Forward Pass and Backward Pass. Forward Pass expresses the process of a forager bee leaving the bee hive and flying towards a food source while Backward Pass denotes the process of a forager bee returning to the bee hive and sharing the food source information with other forager bees (role change). Jatoth and Rajasekhar (2010) hybridised GA and ABCA. Zhao et al. (2010b) also incorporated GA with ABC. Main idea of the approach is to obtain the parallel computation merit of GA; the speed and self improvement merits of ABC by sharing information between GA population and ABC population. Duan et al. (2010) adopted ABC to increase the local search capacity as well as the randomness of the populations with the quantum evolutionary algorithm (QEA). In this way, the improved QEA can jump out of the local optimum and find the global optimal value.

4.4 Miscellaneous

As the ABCA was designed to apply on continuous optimisation problems, it was hard to apply ABC on the optimisation problems where variables can have binary values only. Kashan et al. (2012) proposed a novel ABCA called DisABC for binary optimisation. In DABC algorithm they used the general approach to initialise the variables in binary domain simply by generating a random number in $(0, 1)$ for each dimension and if the number is less than 0.5 then corresponding bit will be set to 0, otherwise bit will be set to 1. Then they used Jaccard's coefficient of similarity/dissimilarity (Sneath, 1957) concept between binary vectors as a measure to quantify how far the two binary vectors are from each other. Based on this measure a new strategy for differential expression in DisABC is proposed. However this strategy works in continuous space but its consequence is used in a two-phase heuristic to construct a complete solution in binary space and also it contains major characteristics of the original one.

In most of the real world optimisation problems, we have to optimise more than one objective function simultaneously which may be conflicting in nature also. In single optimisation problem, we simply seek to achieve a single solution as the search space is totally ordered but, in multiobjective problems, we do not get a single solution as the search space is only partially ordered, instead there exists a set of solutions in which, no solution is better than the other solution in the set, called Pareto optimal solutions. To use the existing ABCA qualities like simplicity, easy to implement, less parameter, Zou et al. (2011) proposed multiobjective artificial bee colony (MOABC) to solve multiobjective optimisation problems. In the proposed algorithm, authors used the Pareto dominance principle to store non-dominated solutions in external archive (EA). The external archive's members are considered as food source positions, associated bees are termed as onlooker bees and there do not exist employed and scout bees. To maintain diversity in the population they used comprehensive learning strategy to produce new solutions v_i in the onlooker bees phase. For each generation, onlooker randomly selects

m dimensions and a food source from external archive to generate a new food source using the following equation:

$$v_{if(m)} = x_{i,f(m)} + \phi(m)\left(EA_{k,f(m)} - x_{i,f(m)}\right) \tag{18}$$

where $k \in \{1, 2, ..., p\}$ is randomly chosen index from p external archive solutions, $f(m)$ is the first m integers of a random permutation of the integers $1 : D$ (dimension of problem) and $\phi(m)$ produces m random numbers correspond to above m generated dimensions, between $[0, 2]$. Each remaining dimension is updated from the other non-dominated solutions through following equation:

$$v_{ij} = x_{ij} + \phi_{ij}(EA_{lj} - x_{ij}) \tag{19}$$

where $l \neq k \in \{1, 2, ..., p\}$ and $j \neq f(m)$. After producing new solution v_{ij} they applied greedy selection technique to decide which solution enters EA. In order to maintain uniform distribution among the archive members and to take care of size of external archive, authors avoided crowded members by estimating the density of solutions in the external archive called crowding distance.

In the same year, Akbari et al. (2012) also proposed a multi-objective ABCA (MOABC) for solving multi modal and multiobjective optimisation problems but they included all three (employed, onlooker and scout) bees phases in their algorithm as compared to above paper which considered only onlooker bee phase not the other bee phases. This MOABC is also a Pareto-based algorithm with an external archive to store non-dominated solutions. In the proposed algorithm, the employed bees adjust their trajectories based on the non-dominated solutions maintained in the external archive by using following equation:

$$v_{ij} = x_{ij} + w_1 r(x_{ij} - x_{kj}) \tag{20}$$

where i represents the food source which is going to be optimised, $k \neq i$ is any archive member and $j \in \{1, 2, ..., d\}$ are randomly chosen indices. r is a uniform random number between 0 and 1 which controls the production of neighbour food sources around x_{ij}. The coefficient w_1 controls the effect of the food source k while producing v_{ij}. The onlooker bee uses the same equation to update its position but the probability with which it selects one of the employed bee, differs as in basic ABC and is given by the equation:

$$p_i = \frac{fit(x_i)}{\sum_{i=1}^{SN} fit_i} \tag{21}$$

where $fit(x_i) = \frac{dom(i)}{foodnumber}$ is the probability of the food source proposed by the employed bee i and $dom(i)$ gives the number of food sources dominated by i^{th} food source. To maintain the archive, they used an ϵ-dominance method (Deb et al., 2005) in which a user defined parameter known as ϵ is responsible towards the size of the final external archive and it guarantees that the retained solutions are non-dominated with respect to all solutions generated during the execution of the algorithm. Further, to control the diversity over the external archive, the authors used a grid-based approach.

Narasimhan (2009) and Subotic et al. (2010) applied the parallelisation in artificial bee colony (PABC) algorithm. Narasimhan (2009) designed parallel implementation of the ABC for a shared memory architecture in which the entire colony of bees is divided equally among the available processors. Each processor has a set of solutions in a local memory. A copy of each solution is also maintained in a global shared memory. During each cycle the set of bees at a processor improves the solutions in the local memory. At the end of the cycle, the solutions are copied into the corresponding slots in the shared memory overwriting the previous copies. The solutions are thus made available to all the processors. They show that the parallel system is much cheaper to build and its power consumption is significantly smaller than single system.

Pampara and Engelbrecht (2011) proposed three versions of ABC that enable it to be applied to optimisation problems with binary-valued domains. The first version is binary ABC (binABC) which is developed by inspiring from the binary PSO developed by Kennedy and Eberhart (1995) and the binary DE developed by Pampara et al. (2005). The main difference between binary PSO and binABC is of position updated equation of bee as with the binary PSO, position updated is done by using velocity updation, but in binABC binary solution is obtained by applying following equation, here bee position is updated instead of velocity:

$$x_{ij}(t+1) = \begin{cases} 0 \text{ if } r_{ij}(t) \geq f(x_{ij}(t)) \\ 1 \text{ if } r_{ij}(t) < f(x_{ij}(t)) \end{cases} \tag{22}$$

here, $x_{ij}(t+1)$ is an updated bee position, $x_{ij}(t)$ is the current position of the bee, $r_{ij}(t)$ is random number between 0 and 1 sampled from a uniform distribution and $f(x_{ij}(t)) = \frac{1}{1+e^{-x_{ij}}}$. The second version is normalised ABC (normABC), which is based on the normalised DE algorithm developed by Pampara et al. (2005). A bit string solution is generated using following equation:

$$b_{ij}(t) = \begin{cases} 0 \text{ if } x'_{ij}(t) < 0.5 \\ 1 \text{ otherwise} \end{cases} \tag{23}$$

here x'_{ij} evolves by first normalising the solution represented by individual. That is, each component of individual is linearly scaled to the range [0, 1]. This is calculated as follows:

$$x'_{ij} = \frac{x_{ij} + {x_i}^{min}}{|{x_i}^{min}(t)| + {x_i}^{max}(t)} \tag{24}$$

where ${x_i}^{min}$ and ${x_i}^{max}$ are the smallest and largest component values for the i^{th} individual respectively. Finally the third version is angle-modulated ABC (AMABC), which is based on the angle-modulated PSO (Pampara et al., 2005) and the angle-modulated DE (AMDE) (Pampara et al., 2006). These algorithm were applied to a number of optimisation problems, and it was shown that the angle-modulated ABC (AMABC) performed somewhat better than the binary and normalised ABC.

Banharnsakun et al. (2011) introduced a new variant of ABC namely the best-so-far selection in ABCA. To enhance the exploitation and exploration processes, they propose to make three major changes by introducing the best-so-far method, an adjustable search radius, and an objective-value-based comparison method in ABC. In best so far method, author multiplied a term f_b (fitness value of best food source so far) to the step size, while creating neighbourhood solution v_{ij} near x_{ij} and this change made the best-so-far algorithm converge more quickly because the solution will be biased towards best-so-far solution. Although this best-so-far method can increase the local search ability but the chance is that the solution is easily entrapped in a local optimum. In order to resolve this issue, an adjustable search radius which increases global search ability for the scout bee was introduced. In the proposed work, new food sources are randomly generated by the scout bee using following equation, whenever the solution stagnates in the local optimum.

$$v_{ij} = x_{ij} + \phi_{ij}[\omega_{max} - \frac{itration}{MCN}(\omega_{max} - \omega_{min})]x_{ij} \tag{25}$$

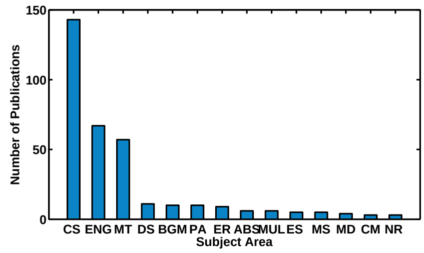
where the value of ω_{max} and ω_{min} represent the maximum and minimum percentage of the position adjustment for the scout bee. The value of ω_{max} and ω_{min} are fixed to 1 and 0.2, respectively by Banharnsakun et al. (2011). The third change is to introduce objective-value-based comparison method in which the objective function value is used for comparison and selection of the better solution rather then comparison of the new and the old solution through the fitness value as in original ABC. Further, the best-so-far ABC is applied in image registration process.

5 Applications of ABC

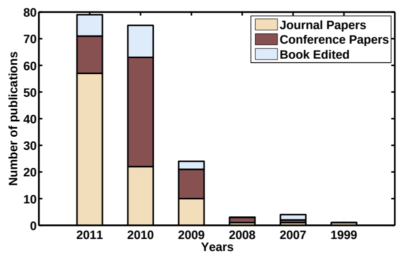
Since its inception, the ABCA has become very popular because of its robustness and ease to apply. Many researchers have successfully applied it on the problems from different application areas. The ABCA was first applied to numerical optimisation problems (Karaboga, 2005). The ABCA was extended for constrained optimisation problems in Karaboga and Basturk (2007a) and was applied to train neural networks (Karaboga and Akay, 2007), to medical pattern classification and clustering problems (Akay et al., 2008). Recently Hsu et al. (2012) used ABC and proposed a personalised auxiliary material recommendation system on Facebook to recommend appropriate auxiliary materials for a learner according to learning style, interests, and difficulty. The object of the proposed method was to search for suitable learning materials effectively. Xing et al. (2007) also studied the control mechanism of local optimal solution in order to improve the global search ability of the ABCA and apply it to solve TSP problems. Singh (2009) used the ABCA for the leaf-constrained minimum spanning tree (LCMST) problem called ABC-LCMST and compared the approach against GA, ACO and tabu search (TS). Rao et al. (2008) applied the ABCA to network reconfiguration problem in a radial distribution system in order to minimise the real power loss, improve voltage profile and balance feeder load subject to the radial network structure in which all loads must be energised. The results obtained by the ABCA were better than the other methods compared in the study, in terms of quality of the solution and computation as efficiency. Bende and Ozkan (2008) used the ABCA for solving direct linear transformation (DLT) which is one of the camera calibration methods by establishing a relation between 3D object coordinate and 2D image plane linearly. Results produced by the ABCA were compared against those of the DE algorithm. Karaboga (2009) used the ABCA in the signal processing area for designing digital IIR filters. Pawar et al. (2008) applied the ABCA to some problems in mechanical engineering including multi-objective optimisation of electro-chemical machining process parameters, optimisation of process parameters of the abrasive flow machining process and the milling process. Recently, machine intelligence and cybernetics are most well-liked field in which ABCA has become a popular strategy.

The bar diagram in Figure 3(a) shows the number of publications in different subject area in which ABC has been successfully applied. In this figure CS stands for computer science, ENG for engineering, MT for mathematics, DS for decision sciences, BGM for biochemistry genetics and molecular biology, PA for physics and astronomy, ER for energy, ABS for agricultural and biological sciences, MUL for multidisciplinary, ES for environmental science, MS for materials science, MD for medicine, CHEM for chemistry and NR stands for neuroscience. Figure 3(b) shows the year wise publication details on ABC. The graph is plotted in stack way in which first part of stack shows the publications in journal, second part shows the publications in conference and third part shows publications in edited books. It is clear from this figure that in last three years the number of publications in ABC research has shown tremendous growth.

Figure 3 (a) Graph showing subject area wise publication of ABC (b) Year wise publication details of ABC (see online version for colours)



(a)



(b)

Source: Scopus dated: 24 June 2012

ABC has been applied to solve many engineering and real world optimisation problems. The use of ABC in the electronics engineering is one of the most interesting field. Image processing is an important branch of electronics engineering. In past, ABC has been used in template Matching in digital images (Chidambaram and Lopes, 2009), image edge enhancement for hybridised smoothening filters (Benala et al., 2009), neural networks training on pattern classification (Karaboga and Basturk, 2009), multilevel image thresholding selection (Horng and Jiang, 2010), segmentation of MR brain images using FCM improved by ABCA (Taherdangkoo et al., 2010), SAR image segmentation (Ma et al., 2011), magnetic resonance brain image classification (Zhang et al., 2011b), multi-circle detection on images (Cuevas et al., 2011), multilevel thresholding selection for image segmentation (Horng, 2011), cloning template designing method for edge detection of CNN-based imaging sensors (Parmaksızoğlu and Alçı, 2011), optimal multi-level thresholding based on maximum Tsallis entropy (Zhang and Wu, 2011b), Face pose estimation (Zhang and Wu, 2011a). Another important field related to electronics engineering is networking. Some of the researchers have applied the ABC to solve cluster-based wireless sensor network routings problem (Karaboga, et al., 2010), efficient load balancing for a resilient packet ring (Bernardino et al., 2010), localisation in wireless sensor networks (Wang et al., 2010a), mapping for application specific network-on-chip design (Deng et al., 2011), minimum routing cost spanning tree problem (Singh and Sundar, 2011), routing and wavelength assignment in optical networks (Kavian et al., 2012). Researchers have applied ABC to solve several applications like, Sensor deployment in irregular terrain (Udgata et al., 2009), a new design method for digital IIR filters (Karaboga, 2009), PAPR reduction method for OFDM signals (Taspinar et al., 2011), sensor deployment in 3-D terrain (Mini et al., 2010), migration of mobile agent (Jiao et al., 2010), CMOS inverter design considering propagation delays (Delican et al., 2010), a novel expression in calculating resonant frequency of H shaped compact microstrip antennas obtained (Akdagli and Toktas, 2010), tackling the static RWA problem (Rubio-Largo et al., 2011), a novel expression for resonant length in calculating resonant frequency of C-shaped compact microstrip antennas (Akdagli et al., 2011), design of multiplier-less non-uniform filter bank transmultiplexer (Manoj and Elias, 2011), enhanced TTCM assisted MMSE multi-user detectors for rank deficient SDMA-OFDM system (Haris et al., 2012), sensor deployment algorithm for target coverage problem in 3-D terrain (Mini et al., 2011), PAPR reduction in OFDM systems (Taspinar et al., 2011), and simple formulas for calculating resonant frequencies of C and H shaped compact microstrip antennas (Toktas et al., 2011).

Further, ABC was used by some researchers to solve electrical engineering optimisation problems like, PID controller tuning (Jones and Bouffet, 2008), economic load dispatch problem with ramp rate limits and prohibited operating zones (Nayak et al., 2009), inverse problems optimisation (Ho and Yang, 2009), direction finding of maximum likelihood algorithm in the impulsive noise (Zhao et al., 2010a), a solution to the optimal power flow (Sumpavakup et al., 2010), speed control of PMSM (Jatoth and Rajasekhar, 2010), transient performance augmentation of grid connected distributed generation (Chatterjee et al., 2010), optimal tuning of PID controllers (Abachizadeh et al., 2010), power loss minimisation in electric power systems (Cobanli et al., 2010), capacitor placement in radial distribution system for loss reduction (Rao, 2010), small signal model parameter extraction of MESFET (Sabat et al., 2010), economic load dispatch problem with non-smooth cost functions (Hemamalini and Simon, 2010), an novel optimal pid tuning and on-line tuning (Gao et al., 2007), optimal power flow with unified power flow controller (Yousefi-Talouki et al., 2010), proportional-integral-derivative controller design (Karaboga and Akay, 2010), reactive power optimisation (Ozturk et al., 2010), partial transmit sequences for peak-to-average power ratio reduction in multi-carrier code division multiple access systems (Karaboga and Akay, 2011b), automatic voltage regulator (AVR) system (Gozde and Taplamacioglu, 2011), synthesis of thinned mutually coupled linear array using inverse fast Fourier transform (Basu and Mahanti, 2011), adaptive filtering (Karaboga and Basturk, 2011), dynamic economic dispatch for units with valve-point effect (Hemamalini and Simon, 2011), model order reduction of single input single output systems (Bansal and Sharma, 2011), real and reactive power tracing in deregulated power system (Sulaiman et al., 2012), optimisation of the automatic generation control (AGC) system (Gozde et al., 2012), optimal reactive power flow (Ayan and Kılıç, 2012) and model order reduction of single input single output systems (Bansal et al., 2012).

There are many optimisation problems encountered in mechanical engineering for which ABC has been applied. The ABC is used in optimised edge potential function (EPF) approach to target recognition for low-altitude aircraft (Xu and Duan, 2010), uninhabited combat air vehicle (UCAV) path planning (Xu et al., 2010). Further, ABC is applied to solve scheduling related problems like resource-constrained project scheduling (Shi et al., 2010), an improved ABCA for job shop problem (Yao et al., 2010), lot-streaming flow shop scheduling problem (Pan et al., 2011), total flowtime minimisation in permutation flow shops (Tasgetiren et al., 2011), flexible job shop scheduling problems (Li et al., 2011c), Pareto-based DABC algorithm for multi-objective flexible job shop scheduling problems (Li et al., 2011d), resource-constrained project scheduling (Ziarati et al., 2011), solve stochastic resource constrained project scheduling problem (Tahooneh and Ziarati, 2011), job shop scheduling using the Best-so-far ABC (Banharnsakun et al., 2012) and order acceptance in two-machine flow shops (Wang et al., 2012). The ABC also used in cylindricity error evaluation (Luo et al., 2009), bottom hole pressure prediction in under balanced drilling (Irani and Nasimi, 2011), parametric optimisation of some non-traditional machining processes (Samanta and Chakraborty, 2011) and multi-objective design optimisation of composite structures (Omkar et al., 2011).

Applications related to computer engineering optimisation problems are very interesting. Some of the applications of ABC related clustering are clustering (Marinakis et al., 2009; Zhang et al., 2010; Karaboga and Basturk, 2011), data clustering (Lei et al., 2010a), fuzzy clustering (Karaboga and Basturk, 2010), A new data clustering approach (Wenping et al., 2010). Some of the researchers used ABC in software testing like software test suite optimisation (Mala et al., 2010; Dahiya et al., 2010), automatic generation of feasible independent paths and software test suite optimisation (Lam et al., 2012). ABC is also used to solve quadratic knapsack (Pulikanti and Singh, 2009) and 0-1 multidimensional knapsack problem (Sundar et al., 2010). The other optimisation problems encountered in computer engineering area for which ABC has been applied are training feed-FNNs (Karaboga et al., 2007), training artificial neural networks (Karaboga and Akay, 2007), solving integer programming problems (Akay and Karaboga, 2009), simulation on travelling salesman problem (TSP) (Hu and Zhao, 2009), solving multiple sequence alignment (Lei et al., 2010b), applied to fusion research in a grid computing environment (Gómez-Iglesias et al., 2010), distributed environments (Banharnsakun et al., 2010) and real time intrusion detection systems (Wang et al., 2010b).

Applications of ABC in civil engineering area are: structural inverse analysis (Kang et al., 2009a), material dynamic parameter back analysis of concrete dams (Kang et al., 2009b), large-scale problems and engineering design optimisation (Akay and Karaboga, 2012a), risk analysis of dam with fuzzy c-means clustering (Li et al., 2011a), optimisation of truss structures (Sonmez, 2011a), reliability analysis of engineering structures (Li et al., 2011b), discrete optimum design of truss structures (Sonmez, 2011b) and leak detection of pipeline (Mandal et al., 2012).

Further, some of the researchers applied ABC to solve various science related optimisation problems. The more focused applications are numerical function optimisation (Karaboga and Basturk, 2007b), black-box optimisation benchmarking for noiseless function testbed using ABCA (El-Abd, 2010), discrete chaos system with rational fraction control (Gao et al., 2010b), online synchronisation of uncertain chaotic systems (Gao et al., 2010a), optimising multi-objective problems (Hedayatzadeh et al., 2010), Loney's Solenoid benchmark problem (Coelho and Alotto, 2011), solving reliability redundancy allocation problems (Yeh and Hsieh, 2011) and accurate global optimisation of numerical functions (Kang et al., 2011). The applications of ABC related to physics and chemistry are protein tertiary structure prediction (Bahamish et al., 2009), modelling daily reference evapotranspiration (Ozkan et al., 2011), S-system models of biochemical networks approximation (Yeh and Hsieh, 2012), prediction of C-peptide structure (Bahamish and Abdullah, 2010), protein structure prediction using the 3DHP-SC model (Vargas Benítez and Lopes, 2010), finding motifs in DNA sequences (González-Álvarez et al., 2011), capping potentials for hybrid quantum mechanical/molecular mechanical calculations (Schiffmann and Sebastiani, 2011) and MRI fuzzy segmentation of brain tissue (Shokouhifar and Abkenar, 2011).

Some heterogenous problems also solved by ABC like Sudoku puzzles (Pacurib et al., 1899), real estate portfolio optimisation based on risk preference coefficient (Hong-mei et al., 2010), forecasting stock markets using wavelet transforms and recurrent neural networks (Hsieh et al., 2011), symbolic regression (Karaboga et al., 2012).

6 Performance review of ABC

In this section, a comprehensive review on performance of ABC as compare to other well-known evolutionary and swarm-based algorithms is presented. The main advantages of ABC are that it is not sensitive to initial parameter values and is not affected by the increasing dimension of the problem (Karaboga and Akay, 2009). For the comparison purpose, researchers used ABC for optimising a large set of numerical test functions and the results produced by ABCA are compared with the results obtained by GA, PSO algorithm, DE algorithm and evolution strategies (ES).

Karaboga and Akay (2009) used 50 benchmark problems in order to test the performance of the GA, DE, PSO and the ABCAs. This set consists of all kinds of problems such as unimodal, multi modal, regular, irregular, separable, non-separable and multidimensional. They performed t-test on pairs of algorithms to diagnose the significant difference among the results of each algorithm, and found that results on functions lying on flat surfaces such as *Stepint* and *Matyas*, by all algorithms have equal performance, since all algorithms have operators providing diversity and variable step sizes.

Krishnanand et al. (2009) showed comparison of five bio-inspired evolutionary optimisation techniques: GA, PSO algorithm, ABCA, invasive weed optimisation (IWO) algorithm and artificial immune (AI) algorithm when applied to some standard benchmark multivariable functions. The experiments showed that for Rosenbrock function the optimum value is not reached by any algorithm. In this case ABC gave better results than other algorithm results. The global minima is reached always in case of ABC and PSO algorithms for small dimensional problems while GA was found to be heavily dependent on the number of function evaluations and Artificial Immune algorithm and IWO techniques performed extremely well for high dimensional problems as compared to the other algorithms. Further, they concluded that, all the applied evolutionary techniques could optimise the given standard benchmark functions to different extents but none of the algorithms were completely successful for optimising all the problems.

Another conclusion that can be drawn was that as the number of variables increases ABC becomes more efficient. There are 14 functions with 30 variables and experiments shows that out of these functions, ABC performs better on 6 than the DE, on 8 than pso and on 14 than GA. Four of the functions on which ABC and DE were unsuccessful were unimodal (Colville, Zakharov, Powell, Quartic). ABC was also unsuccessful on five multi modal functions, while DE was unsuccessful on 9 multi modal functions. Consequently, ABC was provided to be successful and relatively robust on multimodal functions included in the set as compared to DE, PSO and GA. From the results obtained by the experiments, it can be concluded that the performance of ABCA was better or similar to that of these algorithms although it uses less control parameters and it can be efficiently used for solving multi modal and multidimensional optimisation problems.

Basu and Mahanti (2010) presented a comparative study of modified PSO, DE and ABC optimisation in synthesis of circular array problem. In their work, they compared modified PSO, DE and ABC in a statistical manner. Based on pre obtained results and corresponding convergence curves they conclude that if we use ABC, the lowest maximum side lobe level (SLL) value and objective function evaluations are least. Also in this problem, all algorithms achieved the same directivity. They also concluded that in terms of accuracy and convergence time, ABC is superior as compared to modified PSO and Wang et al. (2010a) compared GA and ABCA for localisation in wireless sensor networks and from the simulation results, they found that the ABC requires less time and performs better as compared to GA.

Gozde and Taplamacioglu (2011) compared ABC with PSO algorithm and DE algorithm to AVR system for obtaining optimal control. They found that the ABCA was successfully applied to the AVR system for improving the performance of the controller and shows a better tuning capability than the other similar population-based optimisation algorithms for this control application.

6.1 Computational complexity of ABC

Runtime-complexity analysis of the population-based stochastic search techniques like ABC, PSO, DE is a critical issue in its own right. Zielinski et al. (2005) first investigated the runtime complexity of DE for various stopping criteria, both theoretically and empirically. The time complexity for ABC can also be calculated in the same way. In ABC, there are half the food sources of the colony size (NP). Therefore, for each iteration, a loop over $NP/2$ is conducted in employed bees phase as well as onlooker bees phase containing a loop over D. Thus, if the algorithm is stopped after a fixed number of iterations $Imax$, then the total time complexity of ABC is $O(2 \times (NP/2) \times D \times Imax)$.

Banharnsakun et al. (2011) evaluated the computational complexity of the best-so-far ABCA in comparison with the original ABC and the bee swarm optimisation (BSO) (Akbari et al., 2010) algorithms. The best-so-far ABCA must spend time necessary to find the best-so-far solution in each iteration, so it uses the computational time equal to $(NP/2)D + Imax(3NPD)$ where NP be the total number of bees, D be the dimension of solutions, and $Imax$ be the maximum iteration. They showed that this is larger than the computational time of the original ABCA which is equal to $(NP/2)D + Imax((3/2)NPD + D)$. The BSO algorithm must spend time to sort all bees based on their fitness in each of iteration of algorithm, so the computational time is equal to $NPD + Imax(NP + NPD\log n + (5/2)NPD)$. However, when we focus on the upper bound of the complexity of algorithms, both best-so-far ABC and original ABCAs use computational time $O(ImaxNPD)$ while the BSO algorithm uses $O(ImaxNPD\log n)$, which is the highest complexity.

6.2 Drawbacks of ABC

The inherent drawback with most of the population-based stochastic algorithms is the premature convergence or stagnation. ABC is not an exception. The position update equation in ABC is

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \tag{26}$$

After some iterations, usually all potential solutions work within a very small proximity. In this case the difference $x_{ij} - x_{kj}$ becomes very small and so the improvement in the position becomes negligible. This phenomena is known as the stagnation or premature convergence if the global optimal solution is not present in this small proximity. Any population-based algorithm is regarded as an efficient algorithm if it is fast in convergence and able to explore the maximum area of the search space. In other words, if a population-based algorithm is capable of balancing between exploration and exploitation of the search space, then the algorithm is regarded an efficient algorithm. From this point of view, basic ABC is not an efficient algorithm (Karaboga and Akay, 2009). Karaboga and Akay (2009) compared the different variants of ABC for global optimisation and found that ABC shows a poor performance and remains inefficient in exploring the search space. The problems of premature convergence and stagnation is a matter of serious consideration for designing a comparatively efficient[1] ABCA.

7 Future research perspective with ABC

Although from last two years, a lot of work has been done on ABC, but still there are many open problems and new application areas where it can be applied and of course there exists various dimensions where this algorithm can be modified. Some important future research directions in the area of ABC are as follows:

1 Exploration of the whole search space and exploitation of the near optimal solution region may be balanced by maintaining the diversity in early and later iterations for any random number-based search algorithm. Position update equation (2) in employed bees phase and onlooker bees phase in ABC may be seen in the following way:

$$v_{ij} = A \times x_{ij} + B \times (x_{ij} - x_{kj}) \tag{27}$$

i.e., modified position v_{ij} is the weighted sum of the food source position x_{ij} and the difference $(x_{ij} - x_{kj})$ of two food source positions. Here, A is the weight to target food source and B is the weight to the difference of random food sources. In basic ABC, A is set to be 1, while B is a uniformly distributed real random number (ϕ_{ij}) in the range [–1, 1]. Studies have been carried out with varying (ϕ_{ij}) for better exploration and exploitation mechanism (Akay and Karaboga, 2012b). The new research study can be carried out to set the weight A in the position update equation (27). Furthermore, the range and the value of B can also be fine tuned for better results.

2 A prominent alternative to the best-of-neighbourhood velocity update strategy is the one used in the fully informed PSO algorithm (Mendes et al., 2004). As in the fully informed PSO, a particle is attracted by every other particle in its neighbourhood, the same concept with some modifications can also be applied in the basic ABC. In the basic ABC second term of the position update equation (2), is the difference $(x_{ij} - x_{kj})$ of two food source positions where $k \neq i$. The position update equation of ABC can be modified to take advantage of all the neighbourhood food sources as follows:

$$D_i = (N-1) \times x_{ij} - \sum_{k=1}^{N} x_{kj} \text{ except } k = i \tag{28}$$

Hence the position update equation may be modified as follows:

$$v_{ij} = x_{ij} + \phi_{ij} \times D_i \tag{29}$$

But there are more intensive study required to apply this type of modifications. Akat and Gazi (2008) proposed PSO with dynamic neighbourhood topology. They considered a PSO algorithm in which the neighbours of the particles or basically the neighbourhood topology dynamically changes with time. Probabilistic and distance-based approaches for determining the neighbours of the particles and represent the dynamic neighbourhood topology by a time varying graph were considered. One may also apply similar type of phenomena in the ABC.

3 Improvements also be done by problem dependent fine tuning of ABC control parameters like modification rate of food positions (frequency of perturbation) as shown in equation (14) and *limit* (which prevents ABC process from stagnation). The modification rate (MR), scaling factor (SF) and '*limit*' which are control parameters of the ABCA shown in Akay and Karaboga (2012b) which may be fine tuned for better performance.

4 Efficient modifications in parallel implementation of ABC may be done for improving the performance. It can be observed that many parts of the ABCA can be run in parallel. One way to have a parallel implementation would be to evaluate the fitness for each solution on a different processor. Alternatively, the bees could be distributed among the various processors and allow them to improve the solutions independently. However, this approach would be hindered by the dependencies between the bees. A parallel implementation of the algorithm may be designed for a shared memory architecture, which overcomes these dependencies.

5 In onlooker bees phase of basic ABC, the onlooker bee uses roulette wheel selection scheme in which each slice is proportional in size to the fitness value, to select a food source as shown in equation (3). So in future other fitness-based selection scheme like ranking-based, stochastic universal sampling, tournament selection can be used to calculate probability.

6 In multiobjective optimisation problems we have to optimise two or more than two objective functions simultaneously. As the number of objective functions increases, the conventional Pareto-based MOEAs may perform poorly. In this direction, the multiobjective variants of ABC can be extended for future research.

8 Conclusions

With the increasing complexity of real world optimisation problems, demand for robust, fast, and accurate optimisers is on the rise among researchers from various fields. ABC optimisation algorithm is relatively a recent and simple population-based probabilistic approach for global optimisation over continuous and discrete spaces. It has reportedly outperformed a few EAs and other search heuristics when tested over both benchmark and real world problems although it uses less control parameters and it can be efficiently used for solving multimodal and multidimensional optimisation problems. The main advantage of ABC is that it is not sensitive to initial parameter values and not affected by the increasing dimension of the problem. ABC, like other probabilistic optimisation algorithms, has inherent drawback of premature convergence or stagnation that leads to loss of exploration and exploitation capability of ABC.

this paper attempts to provide a survey on ABC developments, applications and future research perspectives. First, the social behaviour of honey bees is explained step by step and then the simulation of honey bees for ABCAs is shown. Further, in this paper various control parameters of ABC are described with their importance. Next it provided an extensive review of the modifications of ABC based on hybridisation, fine tuning of control parameters and inclusion of new phase/control parameter. After it, a brief overview of various most significant engineering and science applications of ABC are presented. Further, a brief comparison of the performance of ABCA with GA, PSO, DE and ES optimisation algorithms is shown. In, subsequently sections, some drawbacks of ABC and future research perspectives are explained. The content of the paper indicates the fact that ABC will continue to remain a vibrant and active field of multi-disciplinary research in the years to come.

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Notes

1 As it is not possible to design a fully efficient population-based stochastic algorithm.