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Review Article

Optimization Using Artificial Bee Colony Algorithm

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Abstract

Swarm intelligence is briefly defined as the collective behaviour of decentralized and self-organized swarms. The well known examples for these swarms are bird flocks, fish schools and the colony of social insects such as termites, ants and bees. In 1990s, especially two approaches based on ant colony and on fish schooling/bird flocking introduced have highly attracted the interest of researchers. Although the self-organization features are required by swarm intelligence are strongly and clearly seen in honey bee colonies, unfortunately the researchers have recently started to be interested in the behaviour of these swarm systems to describe new intelligent approaches, especially from the beginning of 2000s. During a decade, several algorithms have been developed depending on different intelligent behaviours of honey bee swarms. Among those, artificial bee colony is the one which has been most widely studied on and applied to solve the real world problems. Real-world optimization problems are very difficult and have high degrees of uncertainty. Artificial bee colony algorithm has proved its importance in solving a number of problems including engineering optimization problems. Artificial bee colony algorithm is one of the most popular and youngest member of the family of population based nature inspired meta-heuristic swarm intelligence method. The Artificial bee colony algorithm for solving non-linear problems is presented in the present review.

Keywords: Artificial bee colony algorithm; Meta-heuristic algorithms; Swarm intelligence; Optimization technique.

Introduction

Artificial bee colony algorithm (ABC) developed by Karaboga and further developed by Karaboga and Basturkis a nature inspired algorithm based on the intelligentforaging behaviour of honeybee swarm. The ABC algorithm describes the foraging behaviour, learning, memorizing and information sharing characteristics of honeybees.

The colony of artificial bees consists of three groups of bees: Employed bees, Onlookers bees and Scouts bees [1]. The colony of the artificial bees is divided into two groups, first half of the colony consists of the employed artificial bees and the second half includes the onlooker bees. After the invention of ABC by Karaboga in 2005, the fist conference paper introducing ABC was published in 2006. The first journal article describing ABC and evaluating its performance was presented [2], in which the performance of ABC was compared to GA, PSO and particle swarm inspired evolutionary algorithm. In 2008, the second article presenting a performance evaluation of ABC was published by Karaboga and Basturk (2008) [1]. In 2009, a public domain web-site (http://mf.erciyes.edu.tr/abc) dedicated to ABC was constructed. There are several source codes, written in different programming languages, of ABC and many publications about the modifications to ABC and their applications are presented in the website. The main algorithm of ABC is relatively simple and its implementation is, therefore, straightforward for solving optimization problems and ABC has been found to be very effective in the studies above, being able to produce very good results at a low computational cost. Therefore, after these initial publications many studies have been carried out on ABC [3,4].

Artificial bee colony: ABC-approach

General features of intelligent swarms

There are so many kinds of swarms in the world. It is not possible to call all of them intelligent or their intelligence level could be vary from swarm to swarm. Self-organization is

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a key feature of a swarm system which results collective behaviour by means of local interactions among simple agents [2]. Bonabeau et al. (1999) [5] interpreted the self-organization in swarms through four characteristics:
(i) *Positive feedback*: promoting the creation of convenient structures. Recruitment and reinforcement such as trail laying and following in some ant species can be shown as example of positive feedback.
(ii) *Negative feedback*: counterbalancing positive feedback and helping to stabilize the collective pattern. In order to avoid the Saturation which might occur in terms of available for agers a negative feedback mechanism is needed.
(iii) *Fluctuations*: random walks, errors, random task switching among swarm individuals which are vital for creativity. Randomness is often significant for emergent structures since it enables the discovery of new solutions.
(iv) *Multiple interactions*: agents in the swarm use the information coming from the other agents so that the information spreads throughout the network. Additional to these characteristics, performing tasks simultaneously by specialized agents, called division of labour, is also an important feature of a swarm as well as self-organization for the occurrence of the intelligence [2].

According to Millonas, in order to call a swarm intelligent, the swarm must satisfy the following principles [6].
(i) The swarm should be able to do simple space and time computations (the proximity principle).
(ii) The swarm should be able to respond to quality factors in the environment (the quality principle).
(iii) The swarm should not commit its activities along excessively narrow channels (the principle of diverse response).
(iv) The swarm should not change its mode of behaviour upon every fluctuation of the environment (the stability principle).
(v) The swarm must be able to change behaviour mode when needed (the adaptability principle) [2].

Foraging behaviour of honey bees

The minimal model of forage selection that leads to the emergence of collective intelligence of honey bee swarms consists of three essential components: food sources, employed for agers and unemployed for agers, and the model defines two leading modes of the behaviour: the recruitment to a rich nectar source and the abandonment of a poor source.
(i) *Food Sources*: The value of a food source depends on many factors such as its proximity to the nest, its richness or concentration of its energy, and the ease of extracting this energy. For the sake of simplicity, the “profitability” of a food source can be represented with a single quantity.
(ii) *Employed foragers*: They are associated with a particular food source which they are currently exploiting or are “employed” at. They carry with them information about this particular source to the hive and the information can be the distance and direction from the nest, the profitability of the source and share this information with a certain probability.
(iii) *Unemployed foragers*: They are continually at look out for a food source to exploit. There are two types of unemployed foragers: scouts, searching the environment surrounding the nest for new food sources and onlookers waiting in the nest and establishing a food source through the information shared by employed foragers. The mean number of scouts averaged over conditions is about 5–10% of other bees [2].

Working of Scout Bee

The Scout Bees fly randomly for the search of food. After exhausting their energy and their distance limits they return back to the hive and share their exploration experience with forager bees. The scouts tell the forager about the location of rich food sources. This is done using a dance, Called “waggle dance” which is in the shape of mathematical digit “8”. It also defines the food’s quality [2].

Working of Forager Bees

The forager bees closely notice the scout bee so as to learn all the directions and information given by scout. It then goes to collect food [2].In the case of honey bees foraging behaviour, the four characteristics defined on which self-organization relies can be expressed as follows:
(i) *Positive feedback*: As the nectar amount of a food source increases, the number of onlookers visiting it increases proportionally.
(ii) *Negative feedback*: The exploitation process of poor food sources is stopped by bees.
(iii) *Fluctuations*: The scouts carry out a random search process for discovering new foodsources.
(iv) *Multiple interactions*:
Employed bees share their information about food sources with their nest mates (onlookers)

waiting on the dance area. When the foraging behaviour of honey bees explained above is re-examined, it is seen that the principles defined by Millonas (1994) are fully satisfied [6].

Algorithmic structure of ABC

As in the minimal model of forage selection of real honey bees, the colony of artificial bees in ABC contains three groups of bees: employed bees associated with specific food sources, onlooker bees watching the dance of employed bees within the hive to choose a food source, and scout bees searching for food sources randomly. Both onlookers and scouts are also called unemployed bees. Initially, all food source positions are discovered by scout bees.
Thereafter, the nectar of food sources are exploited by employed bees and onlooker bees, and this continual exploitation will ultimately cause them to become exhausted. Then, the employed bee which was exploiting the exhausted food source becomes a scout bee in search of further food sources once again. In other words, the employed bee whose food source has been exhausted becomes a scout bee.

In ABC, the position of a food source represents a possible solution to the problem and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution [4]. In the basic form, the number of employed bees is equal to the number of food sources (solutions) since each employed bee is associated with one and only one food source.
The general Algorithmic structure of the ABC optimization approach as follows:

Initialize all parameters;

Repeat while Termination criteria is not meet

Step 1: Employed bee phase for computing new food sources.

Step 2: Onlooker bees phase for updating location the food sources based on their amount of nectar.

Step 3: Scout bee phase for searching new food sources in place of rejected food sources.

Step 4: Memorize the best food source identified so far.

End of while

Output: The best solution identified so far [7].

In the initialization phase, the population of food sources (solutions) is initialized by artificial scout bees and control parameters are set. In the employed bees phase, artificial employed bees search for new food sources having more nectar within the neighbourhood of the food source in their memory. They find a neighbour food source and then evaluate its fitness. After producing the new food source, its fitness is calculated and a greedy selection is applied between it and its parent. After that, employed bees share their food source information with onlooker bees waiting in the hive by dancing on the dancing area.

In the onlooker bees phase, artificial onlooker bees probabilistically choose their food sources depending on the information provided by the employed bees. For this purpose, a fitness based selection technique can be used, such as the roulette wheel selection method. After a food source for an onlooker bee is probabilistically chosen, a neighbourhood source is determined, and its fitness value is computed. As in the employed bees phase, agreedy selection is applied between two sources [8].

In the scout bees phase, employed bees whose solutions cannot be improved through a predetermined number of trials, called "limit", become scouts and their solutions are abandoned. Then, the scouts start to search for new solutions, randomly. Hence, those sources which are initially poor or have been made poor by exploitation are abandoned and negative feedback behaviour arises to balance the positive feedback. These three steps are repeated until a termination criteria is satisfied, for example a maximum cycle number or a maximum CPU time [8].

Working principle of ABC

In the ABC algorithm, the position of a food source represents a possible solution of the optimization problem and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution. The number of the employed bees or the onlooker bees is equal to the number of solutions in the population. At the first step, the ABC generates a randomly distributed initial population $P(G = 0)$of SN solutions (food source positions), where SN denotes the size of population [9].

Each solution (food source) $x_i (i = 1,2,\dots,SN)$ is a D-dimensional vector. Here, D is the number of optimization parameters. After initialization, the population of the positions (solutions) is subjected to repeated cycles, $C = 1, 2, \dots, C_{max}$, of the search processes of the employed bees, the onlooker bees and scout bees. An artificial employed or onlooker bee probabilistically produces a modification on the position (solution) in her memory for finding a new food source and tests the nectar amount (fitness value) of the new source (new solution). In case of real bees, the production of new food sources is based on a comparison process of food sources in a region depending on the information gathered, visually, by the bee. In our model, the production of a new food source position is also based on a comparison process of food source positions. However, in the model, the artificial bees do not use any information in comparison. They randomly select a food source position and produce a modification on the one existing in their memory as described in [2]. Provided that the nectar amount of the new source is higher than that of the previous one the bee memorizes the new position and forgets the old one. Otherwise she keeps the position of the previous one. After all employed bees complete the search process, they share the nectar information of the food sources (solutions) and their position information with the onlooker bees on the dance area. An onlooker bee evaluates the nectar information taken from all employed bees and chooses a food source with a probability related to its nectar amount. As in the case of the employed bee, she produces a modification on the position (solution) in her memory and checks the nectar amount of the candidate source (solution). Providing that its nectar is higher than that of the previous one, the bee memorizes the new position and forgets the old one [10].

An onlooker bee chooses a food source depending on the probability value associated with that food sourcep_i, calculated by the following expression (1):

$$p_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n}, \qquad (1)$$

where $fit_i$is the fitness value of the solution $i$evaluated by its employed bee, which is proportional to the nectar amount of the food source in the position $i$and SN is the number of food sources which is equal to the number of employed bees (BN). In this way, the employed bees exchange their information with the onlookers [10].

In order to produce a candidate food position from the old one, the ABC uses the following expression (2):

$$v_{ij} = x_{ij} + \varphi_{ij}(x_{ij} - x_{kj}), \qquad (2)$$

where $k \in \{1, 2, \ldots, BN\}$ and $j \in \{1, 2, \ldots, D\}$ are randomly chosen indexes. Although $k$is determined randomly, it has to be different from i. $\varphi_{i,j}$ is a random number between$[-1, 1]$. It controls the production of a neighbour food source position around $x_{i,j}$and the modification represents the comparison of the neighbour food positions visually by the bee. Equation 2shows that as the difference between the parameters of the $x_{i,j}$ and $x_{j,k}$decreases, the perturbation on the position $x_{i,j}$decreases, too. Thus, as the search approaches to the optimum solution in the search space, the step length is adaptively reduced. If a parameter produced by this operation exceeds its predetermined limit, the parameter can be set to an acceptable value. In this work, the value of the parameter exceeding its limit is set to its limit value.

The food source whose nectar is abandoned by the bees is replaced with a new food source by the scouts. In the ABC algorithm this is simulated by randomly producing a position and replacing it with the abandoned one. In the ABC algorithm, if a position cannot be improved further through a predetermined number of cycles called limit then that food source is assumed to be abandoned [9].

After each candidate source position $v_{i,j}$is produced and then evaluated by the artificial bee, its performance is compared with that of$x_{i,j}$. If the new food has equal or better nectar than the old source, it is replaced with the old one in the memory. Otherwise, the old one is retained. In other words, a greedy selection mechanism isemployed as the selection operation between the old and the current food sources.

ABC algorithm in fact employs four different selection processes:

(1) a global selection process used by the artificial onlooker bees for discovering promising regions as described by (1),

(2) a local selection process carried out in a region by the artificial employed bees and the onlookers depending on local information (in case of real bees, this information includes the colour, shape and fragrance of the flowers) (bees willnot be able to identify the type of nectar source until they arrive at the right location and discriminate among sources *growing* there based on their scent) for determining a neighbour food source around the source in the memory as defined in [2],

(3) a local selection process called greedy selection process carried out by all bees in that if the nectar amount of the candidate source is better than that of the present one, the bee forgets the present one and memorizes the candidate source. Otherwise, the bee keeps the present one in the memory.
(4) a random selection process carried out by scouts.
It is clear from the above explanation that there are three control parameters used
in the basic ABC: The number of the food sources which is equal to the number ofemployed or onlooker bees (SN), the value of *limit* and the maximum cycle number (MCN) [12].

In the case of honey bees, the recruitment rate represents a *measure* of how quickly the bee colony finds and exploits a newly discovered food source. Artificial recruiting could similarly represent the measurement of the speed with which the feasible solutions or the good quality solutions of the difficult optimization problems can be discovered. The survival and progress of the bee colony are dependent upon the rapid discovery and efficient utilization of the best food resources. Similarly, the successful solution of difficult engineering problems is connected to the relatively fast discovery of good solutions especially for the problems that need to be solved in real time. In a robust search process, exploration and exploitation processes must be carried out together. In the ABC algorithm, while onlookers and employed bees carry out the exploitation process in the search space, the scouts control the exploration process. It is clear from the above explanation that there are three control parameters used in the basic ABC: The number of the food sources which is equal to the number of employed or onlooker bees (SN), the value of limit and the maximum cycle number (MCN) [13].

In the case of honey bees, the recruitment rate represents a measure of how quickly the bee colony finds and exploits a newly discovered food source. Artificial recruiting could similarly represent the measurement of the speed with which the feasible solutions or the good quality solutions of the difficult optimization problems can be discovered [14]. The survival and progress of the bee colony are dependent upon the rapid discovery and efficient utilization of the best food resources. Similarly, the successful solution of difficult engineering problems is connected to the relatively fast discovery of good solutions especially for the problems that need to be solved in real time. In a robust search process, exploration and exploitation processes must be carried out together. In the ABC algorithm, while onlookers and employed bees carry out the exploitation process in the search space, the scouts control the exploration process in figure 1 [13].

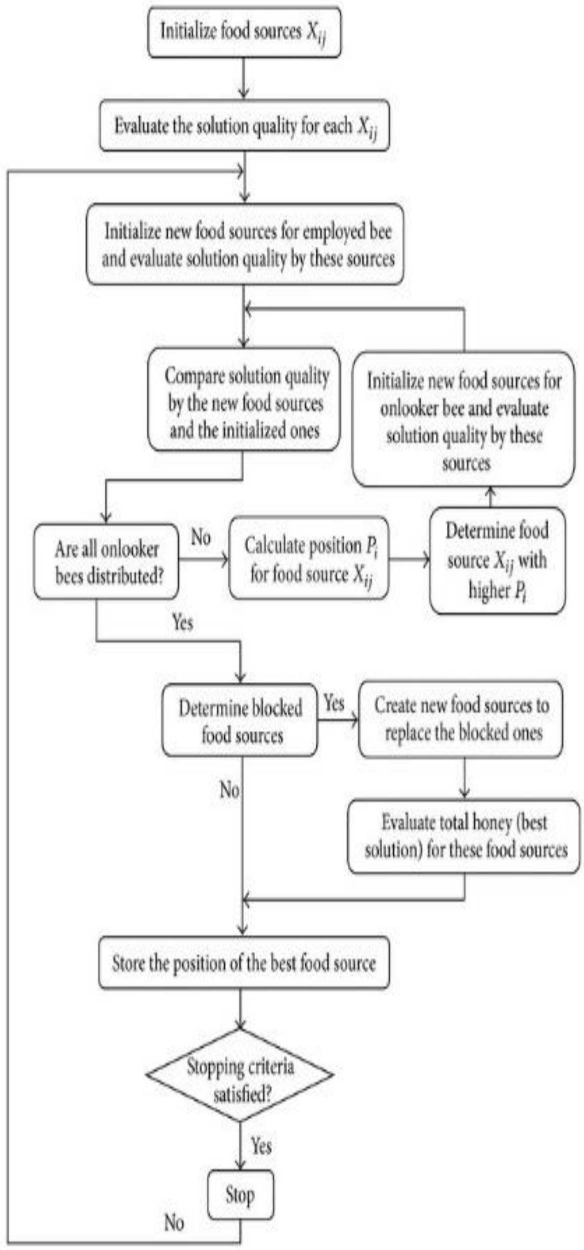

Figure 1. Flow chart for foraging process of honey bees.

Advantages of ABC algorithm

The ABC algorithm has been applied to many real world applications, for example, function optimization, real parameter optimization, digital filter design, clustering, and neural network training. The major advantages which ABC holds over other optimization algorithms are: (i) Simplicity, flexibility and robustness (ii) Use of fewer control parameters compared with many other search techniques (iii) Ease of hybridization with other optimization algorithms (iv) Ability to handle the objective cost with stochastic nature (v) Ease of implementation with basic mathematical and logical operations and (vi) Finding global optimization solution [16-17].

Conclusions

The aim of the present paper is to overview the state-of-the-art research on the ABC algorithm. The ABC algorithm was explained and the key features highlighted. The ABC algorithm out performed or matched those of some other well-known meta-heuristic algorithms. Furthermore, parameter-tuning in meta-heuristic optimization algorithms influences the performance of the algorithm significantly. Other well-known meta-heuristic algorithms have many parameters to tune. In-contrast, the ABC algorithm has only two parameters (*CS* and *MCN*) to be adjusted. Therefore, the updating of the two parameters towards the most effective values has a higher likelihood of success than other competing meta-heuristic algorithms. It is also observed that many researchers are concentrating on the modifications to the ABC algorithm. Hence, ABC became an interesting algorithm for solving constraint and unconstraint optimization problems and applicable to different applications. The performance of the ABC algorithm shows its superiority and the potential for solving complex real-world problems in future publications.

Conflict of interest

Authors declare there are no conflicts of interest.

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