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A review on Artificial Bee Colony algorithm

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Abstract

In recent years large number of algorithms based on the swarm intelligence has been proposed by various researchers. The Artificial Bee Colony (ABC) algorithm is one of most popular stochastic, swarm based algorithm proposed by Karaboga in 2005 inspired from the foraging behavior of honey bees. In short span of time, ABC algorithm has gain wide popularity among researchers due to its simplicity, easy to implementation and fewer control parameters. Large numbers of problems have been solved using ABC algorithm such as travelling salesman problem, clustering, routing, scheduling etc. the aim of this paper is to provide up to date enlightenment in the field of ABC algorithm and its applications.

Keywords: *Artificial bee colony algorithm; Nature inspired meta-heuristic; Swarm intelligence algorithm.*

1 Introduction

Many optimization algorithms have been developed based on nature-inspired concepts. Evolutionary algorithms (EA) and swarm optimization algorithms are two classes of nature inspired algorithms. EA attempts to simulate the phenomenon of natural evolution [1]. In natural evolution, each species searches for beneficial adaptations in an ever changing environment. Genetic algorithms (GA) and differential evolution (DE) algorithms are the example of EA. A basic GA consists of a random number generator, a fitness evaluation mechanism and genetic operators for reproduction, mutation and crossover operations. The GA algorithm is summarized below:

a. Initialize the population
b. Repeat
c. Evaluation
d. Reproduction
e. Crossover
f. Mutation
g. **Until** requirements are met.

The DE algorithm like genetic algorithm using the similar operators: crossover, mutation and selection. The DE algorithm has been proposed to overcome the main disadvantage of poor local search ability of GA. The main difference in constructing better solutions is that GA relies on crossover while DE relies on mutation operation. The algorithm uses the mutation operation as a search mechanism and selection operation to direct the search toward the prospective regions in the search space. The DE algorithm is summarized below:

a. Initialize population
b. Evaluation
c. Repeat
d. Mutation
e. Recombination
f. Evaluation
g. Selection
h. Until requirements are met.

Swarm intelligence has become a research interest to many scientists of related fields in recent years. The term swarm is used for aggregation of animals like fishes, birds, ants, and bees performing collective behavior. The term swarm intelligence (SI) is defined as the collective behavior of decentralized and self-organized swarms [2]. The intelligence of the swarm lies in the networks of interactions between simple agents, and between agents and the environment. The examples of swarm are bees swarming around their hive; an ant colony is a swarm of ants; a flock of birds is a swarm of birds and crowd is a swarm of people.

PSO algorithm models the social behavior of bird flocking or fish schooling [3]. PSO is a population based stochastic optimization technique and well adapted to the optimization of non-linear function in multi-dimensional space. In PSO, a population of particles starts to move in search space by following the current optimum particle and changing the position in order to find out the optima. The position refers to a possible solution of the function to be optimized and the evaluating the function by particle's position provides the fitness of that solution. The main steps of the procedure are:

a. Initialize the population
b. **Repeat**
c. Calculate the fitness values of particles
d. Modify the best particle in the swarm
e. Choose the best particle
f. Calculation of velocities of particles
g. Update the particle positions
h. **Until** requirements are met.

Yang developed a virtual bee colony algorithm based upon intelligent behavior of honey bee swarms [4] to solve the numerical optimization problems. VBA has been introduced to optimize only the function with two variables. For optimizing multivariable numerical functions, Dervis Karaboga proposed a bee swarm algorithm called artificial bee colony algorithm in 2005 as a technical report for numerical optimization problems [5]. ABC is based upon the intelligent foraging behavior of honey bees.

ABC has following characteristics which makes it more attractive than other optimization algorithms:

- It has few control parameters i.e. population size, limit and maximum cycle number [8].
- It is simple, flexible and robust [6, 7].
- Fast convergence speed.
- It can easily be hybridized with other optimization algorithms.

In recent years, ABC is used for a variety of problems such as constrained optimization [9], in image processing [10], in data mining, in engineering design [11] and many others. Since it was developed, many modifications to the original have been developed according to applications across a wide range of domains.

The main objective of this paper is to present an extensive (but not exhaustive) summary of developments and modification to the original ABC. The overall intention is to provide a good beginning document for researchers with interest in developmental knowledge of ABC and its applications. Furthermore, suggestions for possible future investigations in ABC are also highlighted.

The remaining part of the paper is organized as follows: ABC algorithm is explained in section II. Section III discusses the various modified version of ABC and section IV provides a review of applications of ABC by discipline. Finally the conclusion and future research direction are outlined in section V.

2 Artificial bee colony algorithm

The ABC algorithm is a swarm based, meta-heuristic algorithm based on the foraging behavior of honey bee colonies [5]. The artificial bee colony contains three groups: scouts, onlooker bees and employed bees. The bee carrying out random search is known as scout. The bee which is going to the food source which is visited by it previously is employed bee. The bee waiting on the dance area is an onlooker bee. The onlooker bee with scout also called unemployed bee [8, 13].

In the ABC algorithm, the collective intelligence searching model of artificial bee colony consists of three essential components:

- employed bees
- unemployed foraging bees
- Food sources.

The employed and unemployed bees search for the rich food sources around the hive. The employed bees store the food source information and share the information with onlooker bees. The number of food sources is equal to the number of employed bees and also equal to the number of onlooker bees. Employed bees whose solutions cannot be improved through a predetermined number of trials (that is "limit") become scouts and their solutions are abandoned [5]. Analogously in the optimization context, the number of food sources in ABC algorithm represents the number of solutions in the population. The position of a good food source indicates the position of a promising solution to the optimization problem and the quality of nectar of a food source represents the fitness cost of the associated solution.

2.1 Procedure of ABC

The ABC consists of four main phases:

Initialization Phase:

The food sources, whose population size is SN, are randomly generated by scout bees. Each food source, represented by x_m is an input vector to the optimization problem, x_m has D variables and D is the dimension of searching space of the objective function to be optimized. The initial food sources are randomly produced via the expression (1).

$$\boldsymbol{x_m = l_i + rand\,(0,1) * (u_i - l_i)} \quad \ldots\ldots\ldots \tag{i}$$

Where u_i and l_i are the upper and lower bound of the solution space of objective function, rand (0, 1) is a random number within the range [0, 1].

Employed Bee Phase:

Employed bee flies to a food source and finds a new food source within the neighborhood of the food source. The higher quantity food source is memorized by the employed bees. The food source information stored by employed bee will be shared with onlooker bees. A neighbor food source v_{mi} is determined and calculated by the following equation (2)

$$\boldsymbol{v_{mi} = x_{mi} + \emptyset_{mi}(x_{mi} - x_{ki})} \quad \ldots\ldots.. \tag{ii}$$

Where i is a randomly selected parameter index, x_k is a randomly selected food source, $\emptyset_m$ is a random number within the range [-1, 1]. The range of this parameter can make an appropriate adjustment on specific issues. The fitness of food sources is essential in order to find the global optimal. The fitness is calculated by the following formula (3), after that a greedy selection is applied between x_m and v_m.

$$\boldsymbol{fit_m\,(x_m)} = \begin{pmatrix} \frac{1}{1+f_m\,(x_m)}, f_m\,(x_m)>0 \\ 1+|f_m(x_m)|, f_m\,(x_m)<0 \end{pmatrix} \ldots\ldots \tag{iii}$$

Where $f_m(x_m)$ is the objective function value of x_m.

Onlooker Bee Phase:

Onlooker bees calculates the profitability of food sources by observing the waggle dance in the dance area and then select a higher food source randomly. After that onlooker bees carry out randomly search in the neighborhood of food source. The quantity of a food source is evaluated by its profitability and the profitability of all food sources. P_m is determined by the formula

$$\boldsymbol{p_m = \frac{fit_m(x_m)}{\sum_{m=1}^{SN} fit_m(x_m)}} \quad \ldots\ldots\ldots\ldots \tag{iv}$$

Where $fit_m(x_m)$ is the fitness of x_m.

Onlooker bees search the neighborhood of food source according to the expression (5)

$$\boldsymbol{v_{mi} = x_{mi} + \emptyset_{mi}(x_{mi} - x_{ki})} \quad \ldots\ldots\ldots\ldots\ldots \tag{v}$$

Scout Phase:

If the profitability of food source cannot be improved and the times of unchanged greater than the predetermined number of trials, which called "limit", the solutions will be abandoned by scout bees. Then, the new solutions are randomly searched by the scout bees. The new solution x_m will be discovered by the scout by using the expression (6)

$$\boldsymbol{x_m = l_i + rand\,(0,1) * (u_i - l_i)} \quad \ldots\ldots. \tag{vi}$$

rand (0,1) is a random number within the range [0,1], u_i and l_i are the upper and lower bound of the solution space of objective function.

1 Begin
2 Initialize the solution population x_m , i = 1, . . . , SN
3 Evaluate population
4 cycle = 1
5 Repeat
6 Generate new solutions v_{mi} for the employed bees using (ii) and evaluate them.
7 Keep the best solution between current and candidate
8 Select the visited solution for onlooker bees by their fitness
9 Generate new solutions v_{mi} for the Onlooker bees using (ii) and evaluate them
10 Keep the best solution between current and candidate
11 Determine if exist an abandoned food Source and replace it using a scout bee
12 Save in memory the best solution so far
13 cycle = cycle + 1
14 Until cycle = M C N

Fig. 1: Artificial Bee Colony algorithm

3 Modified versions of ABC

Artificial bee colony algorithm continues to attract the interest of researchers from various fields across the globe and this resulted into a number of modification or enhancement to the basic ABC algorithm.

Karaboga and Basturk were presented ABC optimization algorithm for solving constrained optimization problems [15]. In this work the technique of constrained optimization was integrated into the basic ABC algorithm. The authors used Deb’s rules of handling constrained strategy in ABC selection mechanism. The performance of proposed algorithm was evaluated on a set of constrained problems and compared with state-of-art algorithm. It was concluded that proposed ABC can efficiently be used for solving constrained optimization problems.

The performance of ABC algorithm with the integration shift neighborhood structures and greedy randomized adaptive search heuristic for a generalized assignment problem was investigated by Baykasoglu et al [16]. ABC was extended through integration of the employed and onlooker phases with shift neighborhood structures applied sequentially. The simulation results showed that the proposed ABC can solve small to medium size generalized assignment problems effectively.

Quan and Shi introduced the Improved Artificial-Bee-Colony Algorithm [17]. In this work, a new search cycle operator based on the fixed point theorem of contractive mapping in banach spaces was proposed. The performance of proposed algorithm was tested on ten multivariable benchmark functions. The simulation results revealed that the proposed algorithm possessed an excellent performance in the global optimization and can be efficiently employed to solve multimodal problems with high dimensionality.

The modification of ABC algorithm with three selection techniques was carried out by Bao and Zeng [18]. The authors modified the selection of food sources by onlooker bees in order to avoid the premature convergence and increase population diversity. Three selection techniques include disruptive selection, rank selection, and tournament selection. The performance of modified ABC was tested on four high dimensional numerical optimization functions and was compared with original ABC. The results obtained showed that the proposed ABC performed better than original ABC.

An enhanced ABC optimization algorithm named interactive ABC optimization algorithm was proposed by Tsai et al. [19]. The authors introduced the concept of universal gravitational force for the movement of onlooker bees. This concept was used to enhance the exploration ability of the ABC algorithm. The performance of IABC was tested on five numerical benchmark functions and was compared with original ABC, PSO. The simulation results indicated that IABC performed better and can be efficiently applied to solve combinational optimization problem.

Akay and Karaboga were modified the ABC algorithm to solve the real parameter optimization [20]. The authors modified basic ABC by introducing a control parameter that determines how many parameters to be modified. A scaling factor was also introduced that tuned the step size adaptively. The performance of proposed ABC was compared with basic ABC and state-of-art algorithm in literature. The results demonstrated that modified ABC can solve hybrid function efficiently.

ABC algorithm was also integrated with an adaptive penalty function approach (ABC-AP), to minimize the weight of truss structure [59]. The adaptive penalty function method was used for constraint handling within ABC to improve the effect of Deb's rule. The efficiency was studied in five truss example with fixed geometry and up to 200 elements were used to demonstrate that it is an effective optimization technique for structural designs.

Parallelized ABC with ripple-communication strategy (PABC-RC) for solving numerical optimization problem was proposed by Luo et al. [21]. In this paper, the artificial agents were divided into several independent subpopulations. The ripple communication strategy was used for sharing the information between different sub populations. The performance was tested on three benchmark functions. The simulation result showed that proposed ABC increased the accuracy of ABC on finding the best solution.

A cooperative ABC (CABC) algorithm was introduced by Zou et al. [22]. In this work, the final solutions were produced by using the information from all the populations. Firstly, the proposed algorithm was tested on several benchmark functions and was compared with ABC, PSO. From simulation results, it was concluded that CABC had the ability to attain the global optimum solution. Secondly, the proposed algorithm was applied on clustering problem and was tested on several data sets. The performance was compared with ABC, PSO and k- means. The simulation results illustrated that proposed algorithm is better than other algorithms in terms of average value and standard deviations of fitness function.

Karaboga and Akay were modified the ABC algorithm for constrained optimization problems [23]. The proposed ABC algorithm used Deb's rules, consisting of three simple heuristic rules and a probabilistic selection scheme. The proposed ABC was tested on thirteen well known test problems and results were compared with state-of-art algorithms. The results from these test demonstrated that the proposed algorithm was able to solve the problem.

The concept of adaptive population of food sources for ABC algorithm named ABC-SAC was proposed by Sharma et al. [24]. The ABC-SAC algorithm was further modified by including the elitism selection scheme and incorporating global-local exploration. By analysing the proposed algorithm and its results, the authors claimed that proposed approach looks promising.

A modified version of ABC algorithm to enhance the global searching capability by using differential operator was proposed by Wu and Qian [25]. The uniform distribution capability of differential operator was used by the author to enhance the population diversity of solutions. The proposed algorithm was tested on a set of well-known benchmark functions and the results were compared with original ABC. The performance of proposed ABC was found more effective than original ABC algorithm.

El-Abd was proposed the opposition based ABC algorithm for black box optimization benchmark data [26]. In this work, the performance of ABC was improved by introducing the idea of opposition-based learning. The proposed concept was introduced through the initialization step and through generation jumping. The author tested and compared the performance of OABC with that of ABC and opposition based differential evolution (ODE) using black box benchmark data. The results of the concept revealed better performance than ABC and opposition based differential evolution (ODE) algorithm.

Kashan et al. [60] proposed a new modification to the original ABC called DisABC for binary optimization problems. In this work, a new differential expression was used which utilizes a measure of dissimilarity between binary vectors. The effectiveness of DisABC was tested on a set of 15 benchmark problem instances of uncapacitated facility location problem (UFLP). The result of proposed algorithm was compared with binDE and PSO algorithms. The simulation results showed that the performance of DisABC was good and promising.

An enhanced ABC called fast mutation ABC (FMABC) was proposed by Bi [27]. The authors modified the selection technique with pheromone and sensitivity model. The scout behavior was replaced by mutation strategy from opposition based learning. The performance was evaluated on seven benchmark functions and was compared with basic ABC. The results showed the performance of FMABC as better than that of basic ABC.

Chaotic search based ABC algorithm for solving the accuracy of global optimal value was proposed by Yan and Li [28]. In this paper, the premature convergence problem of basic ABC was solved by increasing the number of scouts and by using chaotic search. The proposed algorithm was applied in PID control tuning. The results showed that CABC had high accuracy and the PID control systems adopted optimal parameters.

Sharma and Pant were proposed a variant of ABC called RABC for solving the numerical optimization problem [29]. The authors applied three different modifications: colony size reduction mechanism during evolutionary process, modified the perturbation scheme and improvement in population diversity by using rank selection strategy. The performance was tested on eight benchmark functions and six shifted functions. The results demonstrated that RABC with appropriate parameters outperformed the ABC algorithm.

A qucik ABC algorithm was proposed by Karaboga and Gorkemli [30]. In this work, a new definition for onlooker bees of ABC algorithm was proposed so that the behavior of foragers of ABC algorithm can be modeled more accurately. The quick ABC was tested on 4-well known benchmark problems and the results obtained were compared with original ABC. Simulation results showed that quick ABC significantly improved the convergence speed and quick ABC can be used for solving combinational optimization problems.

Xu et al. proposed a new artificial bee colony (NABC) algorithm [31]. In this work, the authors enhanced the performance of original ABC by modifying the search pattern of both employed and onlooker bees. A solution pool was constructed by storing some best solutions of the current swarm and new candidate solutions were generated by searching the neighborhood of solutions randomly chosen from the solution pool. The proposed algorithm was tested on a set of twelve benchmark functions. Simulation results showed that the proposed approach was significantly better or at least comparable to the original ABC.

Table 1: summary of modification to ABC algorithm

Algorithm Name	Description of modification	Problem	References
MABC	Incorporated Deb’s rule in selection mechanism	Constrained optimization	[15]
ABC	Integration of GRAH and two neighborhood search equation	Generalized assignment	[16]
IABC	Incorporated new search cycle based up on the fixed point theorem of contractive mapping	Benchmark functions	[17]
MABC	Incorporated three new selection mechanism	Benchmark functions	[18]
IABC	Universal gravitation forces were used to change the movement of onlookers	Numerical optimization	[19]
MABC	Integration of control parameters such as modification rate (MR), scaling factor (SF)	Real parameter optimization	[20]
ABC-AP	Adaptive penalty constraint to enhance Deb’s rule was used in the modification	Weight of truss structure	[59]
PABC-RC	Integration of ripple communication strategy for exchange of information	Numerical optimization	[21]
CABC	Cooperative search technique is used for exchange the information	Data clustering	[22]
MABC	Incorporated Deb’s rule in selection mechanism	Constrained optimization	[23]
ABC-SAC	Used the concept of adaptive population of food sources with elitism selection mechanism	Benchmark function	[24]
MABC	Incorporated the concept of differential operator	Benchmark function	[25]
OABC	Used the concept of opposition number	Black box optimization	[26]
DisABC	Used differential expression to measure dissimilarity between binary vectors	Binary optimization	[60]
FM-ABC	Modified the selection mechanism of ABC with components of free search algorithm	Benchmark functions	[27]
CABC	Used the concept of chaotic search	PID control tuning	[28]
RABC	Incorporated the colony size reduction mechanism, rank selection mechanism and modified the perturbation scheme	Benchmark functions	[29]
Q-ABC	Incorporated the new definition for onlooker bees	Benchmark function	[30]
NABC	Modified the search patterns of both onlooker and employed bees	Benchmark function	[31]

4 Applications of ABC

Large numbers of real-world optimization problems have been solved by the ABC algorithm that demonstrates the utilization and effectiveness of this algorithm. In the following subsection, some areas to which ABC has applied are discussed in detail.
These areas include:

- Benchmark optimization
- Bioinformatics field
- Data Mining
- Engineering design and applications
- Scheduling

4.1 Benchmark Optimization

All of the optimization algorithms are tested using various benchmark functions. Some examples of these optimization problems include:

- unimodal and multi-modal functions
- continuous and discrete variables
- unconstrained and constrained problems

First of all ABC algorithm was evaluated using unimodal and multimodal problems. Other variations of ABC were also developed and evaluated using different benchmark optimization problems [7, 19, 23].

The analysis of behavior of ABC algorithm under different control parameter values was carried out by Karaboga and Bastruk [14]. ABC was noted to produce better results as the population size increases. The results obtained by ABC were also better than EA, PSO, DE. The author also claimed that ABC can be efficiently employed to solve problems with high dimensionality.

A. Singh presented the ABC algorithm for the leaf-constrained minimum spanning tree problem [7].This work was the first application of ABC for a discrete optimization problem and demonstrated the capability of ABC algorithm in solving a discrete optimization problem. In this work, the author slightly changed the process of scout generation of ABC. The Scouts are produced with aid of collision process and the collision process keeps track on duplicate solution in the population. The performance of ABC was tested on 45 Euclidean problem instances and the results compared with the ACO-LMCST, TS_LMCST and SCGA. ABC - LMCST completely out-performed the ACO_LMCST both in terms of solution quality as well as running time.

Karaboga and Akay [8] presented a comparative study of artificial bee colony algorithm. In this work the performance of ABC algorithm was compared with PSO, DE, EA, GA on a larger set of numerical test functions. The simulation results revealed that performance of ABC is better or similar to PSO, DE, EA, GA algorithms with advantage of employing fewer control parameters.

Solving integer programming problems by using artificial bee colony algorithm was presented by Karaboga and Akay [32]. This work studied the application of ABC to integer programming problems (IPP). In order to cope with IPP, solutions were truncated to nearest integer values in neighbor solution production unit. The performance of ABC was compared with those of PSO algorithm variants, Branch and Bound technique. The simulation results revealed that ABC can handle the problems efficiently and can be considered robust by the statistics calculated (i.e. mean, median and standard deviation).

Black box optimization benchmarking for noiseless function test bed using artificial bee colony algorithm was presented by El-Abd [33]. The performance of ABC was tested using the noise free BBOB 2010 test bed. The simulations results revealed that ABC is highly successful in the separable and weak structured functions.

4.2 Bioinformatics field

Finding motifs in DNA sequences applying a multi objective ABC algorithm was presented by Vega Rodriguez et al. [34]. Motif has major application in the specific task of discovering transcription factor binding sites (TFBS) in DNA sequences but motif discovery is an NP- hard problem and to solve this problem author(s) proposed a multi-objective

ABC algorithm (MOABC). The simulation results obtained showed significant improvement than those previously published.

C. Vargas and H. lopes presented parallel artificial bee colony algorithm approaches for protein structure prediction using 3dhp-sc model [35]. Two parallel approaches for the ABC similar to master-slave and hybrid-hierarchical relations were implemented by the authors. ABC parameter was tuned and load balance adjustments are carried out in the course of experiment. The performance of the parallel models was compared with a sequential version for 4-benchmark instances. The simulation results revealed that parallel models achieve good level of efficiency, where the hybrid hierarchical approach improved the quality of solutions obtained.

Using an efficient artificial bee colony algorithm for protein structure prediction on lattice models was presented by Jian lin et al. [36]. In this work the author(s) tried to solve the protein folding problem (PFP). PFP problem is the one of the 125 biggest unsolved problems in science. The author(s) proposed modified ABC algorithm for PFP and demonstrated that this algorithm can be applied successfully to the protein folding problem based on hydrophobic-polar lattice model.

4.3 Data mining

Clustering is the task of grouping a set of objects in such a way that objects in the same group are more similar to each other than to those in other groups. Data clustering problems were previously tackled using a variety of information technology techniques. ABC was also used to solve the clustering problem efficiently. In this regard, mini sensor deployment in irregular terrain using artificial bee colony algorithm was presented by Udgata et al. [37]. The optimal sensor deployment is a problem of maximizing coverage and minimizing number of sensor nodes which has been proved to be NP-hard. This problem was modeled as data clustering problem in which centroid of each cluster represented the position of a sensor node to be deployed and optimal solution was obtained using ABC algorithm. Results obtained showed that ABC algorithm produced robust and good quality of solution.

Karaboga and Ozturk were presented a novel clustering approach using artificial bee colony algorithm [38]. In this work ABC algorithm was used for data clustering on benchmark problems and the performance was compared with previous techniques. Thirteen type of datasets from UCI machine learning repository were used to demonstrate the results of the techniques. The simulation results showed that ABC algorithm can efficiently be used for multivariate data clustering.

Karaboga and Ozturk were presented fuzzy clustering with ABC algorithm [39]. In this work ABC was used for fuzzy clustering and the performance was evaluated using cancer, diabetes and heart benchmark datasets from UCI machine learning repository. The results showed that the performance of ABC in fizzy clustering was good.

Udgata et al. were presented sensor deployment in 3-d terrain using ABC algorithm [40]. In this work author modeled the sensor deployment problem as data clustering problem and the optimal locations for sensor deployment were obtained using ABC algorithm. Sensitive analysis test was carried out to find out the variation in the sensing range if the sensor nodes were deployed in near optimal position. The results showed that ABC algorithm can be used for obtaining the optimal solutions.

Artificial bee colony data miner for classification of data mining was proposed by Celik et al. [41]. In this work, the performance of ABC-miner was evaluated using Wisconsin, zoo and breast benchmark datasets from UCI machine learning repository. The results were compared with PSO rule classification and C4.5 algorithm. The results showed that ABC-miner can efficiently be used for classification task.

Abdulsalam et al. were presented a cluster deviation detection task using the ABC algorithm [42]. In this work ABC was deployed for deviation detection. An outlier factor was used to identify the top n outliers that deviate from the datasets. ABC was tested on three UCI benchmark datasets. The results showed that ABC performed well.

4.4 Engineering Designs and Applications

ABC attracts many researchers to test its performance on a variety of engineering problems. N. Karaboga was presented a new design method based on the ABC algorithm for digital IIR filters [43]. Digital filters can be classified into two type infinite impulse filters (IIR) and finite impulse filters (FIR). IIR perform better than FIR at same number of coefficients but IIR had multi modal error surface. To solve this problem ABC was utilized by the author and the performance was compared with PSO and LSQ-nonlin. The results showed ABC can efficiently handle the problem and can be employed as an alternative technique for designing IIR filters.

Sabat et al. were utilized the ABC algorithm for extracting small signal model parameter of MESFET [44]. Parameter extraction in MESFET process involves reducing the difference between modeled and measured S parameter over a broad frequency range. This problem surface is viewed as a multi-modal error surface and robust optimization algorithms are required to solve this kind of problem. The author(s) utilized the ABC algorithm to solve this problem and the performance was compared with PSO with respect to computational time and quality of solutions. The simulation results illustrated that this technique extract accurately 16-element small signal model parameters. The efficiency of this approach is demonstrated by a good fit between the measured and modeled S-parameter data over 0.5-25 GHz frequency range.

Gozde et al. utilized ABC algorithm in an automatic voltage regulator system [45]. In this work, ABC was utilized to optimize the gains of the PID controller for automatic voltage regulator system. The performance was compared with the PSO and the study showed that ABC algorithm performed better than other population based optimization algorithms.

Chatterjee et al. utilized ABC algorithm for transient performance augmentation of grid connected distributed generation [46]. In this paper, a conventional thermal power system equipped with automatic voltage regulator (AVR), integral controlled automatic generation control loop and IEEE type dual input power system stabilizer (PSS3B) was considered. This hybrid distributed system was connected to the grid. The different tunable parameters of the proposed hybrid power system model were optimized with the help of ABC algorithm. The results offered by the ABC algorithm were compared with those offered by genetic algorithm (GA). It was also revealed that the optimizing performance of the ABC was better than the GA for this specific application.

Ozturk et al. were utilized ABC algorithm for reactive power optimization [47]. Reactive power optimization is an important issue for providing the secure and economic run of the power systems. The authors used multi objective RPO to correct the voltage deviations of buses, active power losses and reactive power generation costs. ABC was applied on ten bus system and the results were compared with the pareto evolutionary algorithm. It was claimed by the author that the system runs more effectively and economically with the results found with ABC.

Omkar et al. utilized ABC for multi-objective design optimization of composite structures [48]. In this study, the authors presented generic method for multi-objective design optimization of laminated composite components. The primary optimization variables were the number of layers, its stacking sequence and thickness of each layer. The design was evaluated using three failure criteria: the tsai-wu failure criteria, failure criteria based on failure mechanism and maximum stress failure criteria. The performance was evaluated in comparison with PSO, genetic algorithms (GA), artificial immune system (AIS). The results showed that the performance of ABC was at par with that of PSO, AIS, GA for all loading configurations.

Safarzadeh et al. utilized ABC for loading pattern optimization of power reactors [49]. In this work, a core reloading technique using ABC was presented in the context of finding an optimal configuration of fuel assemblies. The authors evaluated the technique with the power flattering of a VVER-1000 core considered as an objective function. Other variables such as keff, power peaking factor, burn up and cycle length was also considered. The proposed ABC algorithm was also applied to a core design optimization problem previously solved with genetic algorithm and PSO algorithm. The results showed that ABC performed very well and was comparable to the canonical genetic algorithm and PSO.

Prajapati et al. utilized ABC for multi objective power optimization [50]. Reactive power optimization (RPO) is an important issue in the operation and control of power system. In this paper, authors presented the ABC based optimization technique to handle the RPO problem as a true multi-objective optimization problem with competing objectives. The proposed approach was analyzed and demonstrated on the standard IEEE-30 bus test system. The simulation results proved that proposed approach had great potential to solve the RPO problem.

Akay and Karaboga were presented ABC algorithm for large scale problems and engineering design problems [51]. In this work, ABC algorithm was used for optimizing the large scale and engineering design problems by extending the basic ABC algorithm simply by adding a constraint handling technique in selection process. The proposed ABC was tested on nine well known unconstrained problems and five well known constrained engineering problems, and the performance was compared with previous algorithms.

Optimization of skeletal structural using artificial bee colony algorithm was presented by Talatahari et al. [52]. In this study, ABC algorithm was used to optimize the different skeletal structures. The performance was compared with other optimization algorithm from the literature. The results showed that ABC can efficiently be used in structural design problems.

4.5 Scheduling

Scheduling is the process of deciding how to commit resources between varieties of possible tasks, to basically minimize the total production cost or time.

Yin et al. were presented an efficient job shop scheduling algorithm based on ABC algorithm [53]. Job shop scheduling problem is an NP-hard problem of wide engineering and theoretical background. To solve this problem the authors proposed a new ABC algorithm called discrete ABC algorithm. The proposed algorithm was tested on JSSP benchmarks and the results showed that proposed algorithm was both effective and efficient.

Ajorlou et al. studied the performance of artificial bee colony algorithm approach for optimizing a multiproduct CONWIP-based manufacturing system [54]. In this work, a mixed integer non-linear programming is developed to generate an optimal sequence of jobs and WIP level in a serial constant work in progress (CONWIP) production line in order to minimizing the overall completion time. The proposed algorithm was tested on a numeric example. The results showed that the performance of ABC was good on real world problems involving large number of parts, machines and production lines.

Zhang and Cheng were utilized ABC algorithm for job shop scheduling problem with random processing times [55]. In this paper, the authors proposed ABC algorithm for stochastic job shop scheduling problem with the objective of minimizing the maximum lateness. The performance of proposed algorithm was tested on different scale test problems. The results showed validated the effectiveness and efficiency of the proposed algorithm.

Wang et al. presented an effective ABC algorithm for solving the flexible job-shop scheduling problem with the criterion to minimize the maximum completion time [56]. A well designed left shift decoding scheme was employed to transform a solution to an active schedule. Simulation results based on well-known benchmarks and comparisons with some existing algorithms demonstrated the effectiveness of the proposed ABC algorithm.

Chen and Sung were utilized ABC for aircraft maintenance scheduling [57]. In this work, the problem of airline maintenance scheduling was considered. A maintenance-scheduling model was considered and to solve this model ABC was used by setting the appropriate number of parameters. The simulation results validated the feasibility and practicality of model and ABC algorithm.

Lin and Ying utilized ABC in increasing the total net revenue for single machine order acceptance and scheduling problems [58]. The order acceptance and scheduling problem is an important topic for make-to-order production systems with limited production capacity and tight delivery requirements. The authors proposed a new algorithm based on ABC algorithm for solving this problem. The performance of proposed algorithm was evaluated by a benchmark problem set of test instances up to 100 orders. The simulation results demonstrated that proposed ABC outperformed three stat-of-art algorithms from literature.

Table 2: summary of applications of ABC

Problems	References
Benchmark optimization	7, 8, 14, 32, 33
Bioinformatics	34, 35, 36
Data mining	37, 38 , 39 40, 41, 42
Engineering designs and applications	43, 45, 48, 44, 47, 52, 51, 50, 49, 46
Scheduling	53, 54, 55, 56, 57, 58

5 Discussion and conclusion

In this paper, variety of research article in the domain of ABC has studied. From the in depth literature survey, it is observed that a large part of research was concentrated towards modifying the ABC algorithm to solve a variety of problems, including engineering design problems, scheduling problems, data miming problems etc.

Although ABC has great potential, it was clear to the scientific community that some modifications to the original structure are still necessary in order to significantly improve its performance. New neighbor production mechanisms can be proposed to improve the convergence speed. New schemes for scout generation can be proposed for diversity improvement. New selection techniques can be proposed for distribution of onlookers to the food sources so that the performance of ABC can be enhanced. And also ABC can be used as an evolutionary framework into which different traditional or modern heuristic algorithmic components are integrated.

Like all other evolutionary optimization approaches, ABC also has some drawbacks. For example since it does not use an operator like crossover in GA or DE, the distribution of good information between solutions is not at a required level. This causes the convergence performance of ABC for local minimum to be slow. This topic can be searched and its convergence performance can be improved.

In conclusion, ABC remains a promising and interesting algorithm, which would be used extensively by the researchers across diverse fields.

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