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A Review on Artificial Bee Colony Algorithms and Their Applications to Data Clustering

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Abstract: *Data clustering is an important data mining technique being widely used in numerous applications. It is a method of creating groups* (*clusters*) *of objects, in such a way that objects in one cluster are very similar and objects in different clusters are quite distinct, i.e. intra-cluster distance is minimized and inter-cluster distance is maximized. However, the popular conventional clustering algorithms have shortcomings such as dependency on center initialization, slow convergence rate, local optima trap, etc. Artificial Bee Colony* (*ABC*) *algorithm is one of the popular swarm based algorithm inspired by intelligent foraging behaviour of honeybees that helps to minimize these shortcomings. In the past, many swarm intelligence based techniques for clustering were introduced and proved their performance. This paper provides a literature survey on ABC, its variants and its applications in data clustering.*

Keywords: *Data clustering, swarm intelligence, artificial bee colony, meta-heuristics, optimization.*

1. Introduction

Swarm Intelligence (SI) is an emerging research field inspired by collective intelligence of social insects or animals in group, such as ant colonies, bee colonies, bird flocks, fish schools and so on. The concept of collective intelligence was originally introduced in [1] to discuss the self-organizing and intelligent behavior of ants and explain how the ants choose between different routes to food sources with varying quality. However, the concept was gradually discarded and it started reemerging in the late 1980s with the increase in research on artificial life and complex systems theory. Collective intelligence may be considered as the collection of large number of agents that interact among themselves, as well as active environment to generate adaptive behavior [2]. The term “swarm intelligence” was introduced in the context of cellular robotic systems [3]. The relation between an individual and the society was better explained in terms of collective exploration and group behavior of social insects. Their incredible characteristics such as self-organization, collective decisions, division of labor, positive and negative feedback play a major role in designing of complex systems for numerous applications [4]. A modern concept of collective intelligence was provided in terms of swarm as "*a swarm is a set of (mobile) agents which are liable to communicate directly or indirectly (by acting on their local environment) with each other, and which collectively carry out a distributed problem solving*" [5]. In addition, they describe Swarm Intelligence as "*a property of non-intelligent agents exhibiting collectively intelligent behavior*".

Swarm Intelligence is also defined as "*any attempt to design algorithms or distributed problem-solving devices inspired by the collective behavior of social insect colonies and other animal societies*" [6]. Hinchey, Sterritt and Rouff [7] have defined swarm as "*a large group of simple components working together to achieve a goal and produce significant results*". Some authors in [8] have described swarm intelligence in the context of both humans and animals as "*two or more individuals independently, or at least partially independently, acquire information and these different packages of information are combined and processed through social interaction, which provides a solution to a cognitive problem in a way that cannot be implemented by isolated individuals*". Most widely used SI algorithms developed during recent years are: Ant Colony Optimization, which is based on ant colonies [9], Particle Swarm Optimization, which is based on fish schooling/bird flocking [10], Immune Algorithm, which is based on swarm of cells and molecules [11], Bacterial Foraging Optimization, which is based on E. Coli bacteria foraging (see [12]), Artificial Bee Colony, which is based on honey bee swarms [13], Cat Swarm Optimization, which is based on behavior of cats [14], Cuckoo Search Algorithm [15], Firefly Algorithm, which is based on flashing behavior of tropical fireflies [16], Gravitational Search Algorithm which is based on interaction of masses [17] and many more.

In this digital era, it is really challenging to store, process and analyze the huge and rapidly increasing data without appropriate tools or techniques. Data mining is the process of extracting useful information and knowledge by exploring and analyzing this data using analytical algorithms or means. Clustering or cluster analysis is a form of indirect data mining, as the goal is to find the relationships among all the variables in contrast to direct data mining, where some variables are pointed out as targets [18]. Clustering is an important and popular data mining task. It can be regarded as a form of unsupervised classification i.e. labeling of objects does not rely on predefined classes, rather it derives from the data itself [19, 20]. Clustering is a method of creating groups (clusters) of objects, in such a way that objects in one cluster are very similar (or related) and objects in different clusters are quite distinct (or unrelated). This process mainly consists of four steps. In the first step, distinguishing features are selected from a set of candidates and then extracted using some transformations. The second step is to select a proximity measure and construction of a criterion function. Third step is defining testing criteria for cluster validation and finally, the results are interpreted to check reliability of useful information [21]. Clustering is widely used in numerous applications, including market research, pattern recognition, data analysis, document retrieval, image segmentation, artificial intelligence, bioinformatics, classification of coals, financial investment, data compression, web mining, machine learning and image processing [22-24].

Objects similar to each other are identified in a cluster or group of a data set (different from those in other clusters/groups) using clustering techniques. Euclidean distance is the most used similarity metric derived from the Minkowski metric; the lesser the distance, more similarity is there between two objects or two clusters. Clustering is categorized as hard clustering and fuzzy clustering. Hard clustering is sub-categorized as hierarchical clustering and partitional clustering [18, 23]. In hierarchical clustering objects are gradually (dis)assembled into clusters whereas objects are iteratively relocated to form clusters of proper convex shapes in partitional clustering. Hierarchical clustering can be divided into agglomerative methods and divisive methods. Agglomerative (bottom-up) clustering begins with each object as a separate cluster and starts merging the most similar clusters recursively according to some criteria [25]. Divisive (top-down) clustering begins with the whole data set in one cluster and splits it into successively smaller clusters. Clearly, this method is less frequently used than agglomerative method since poor choices at early stages may not provide optimal solutions [26]. However, there may be drawbacks in both methods: incorrect grouping of data points at early stage that may not be reallocated, difficulty of choosing right stopping criteria, different measures for similarity between clusters generating different results [18, 27, 28].

Partitional algorithms divide the set of data in clusters by iteratively relocating objects without hierarchy. The clusters are gradually improved to ensure high quality of clustering. The clusters are formed in such a way that each cluster contains at least one data object and each data object belongs to exactly one cluster [29]. Fisher [30] expressed the set of data elements into groups such that squared distance (sum of squares) within each group is minimized. The one-dimensional approach involved in the process may be used to solve N-dimensional grouping. An early version of k-Means was proposed by Forgy [31] called as two step method of clustering. The method reassigns the data points to their nearest cluster centres in first step, while the centres of the newly formed groups are recomputed in the next stage. The process continues until convergence criterion is met. Macqueen [32] defined the k-Means to generate partitions of an N-dimensional population such that each partition is having small within-class variance. The centres of so formed partitions are continuously updated with the assignment of data points to different partitions. In k-Means, each cluster has a centre called mean and attempt is made to minimize its objective function (a square error function). The objective function for a set of data objects $X = \{x_1, ..., x_N\}$, K disjoint subsets c_j is given as

$$KM(X, C) = \sum_{i=1}^{N} \min\left\{\left\|x_i - c_j\right\|^2 \mid j = 1, ..., K\right\}. \quad (1)$$

The k-Means algorithm also has some limitations: dependence on initialization of cluster centers, sensitivity to outliers, non-guaranteed optimal solutions, formation of unbalanced clusters [22, 28, 33]. There have been several approaches to overcome the above shortcomings, which are based on swarm, insects and natural phenomena. A Genetic k-Means algorithm was proposed in [34] that makes use of a search operator and a biased mutation operator to find global optimal solutions in clustering. Garai and Chaudhuri [35] introduced a two-phase genetically based clustering algorithm. The data is first decomposed into a large number of clusters using Cluster Decomposition Algorithm and then combined using Hierarchical Cluster Merging Algorithm. During the process, genetic algorithm is applied on fragmented clusters in several cycles to find the final partitions. One GA-clustering algorithm integrating the capability of GA with the simplicity of k-Means was developed to avoid the sub optimal solutions in clustering [36]. A genetic algorithm exchanging neighboring centers for k-Means clustering was proposed in [37]. Selim and Alsultan [38] introduced a simulated annealing algorithm for data clustering. A number of algorithms based on tabu search method have been proposed for data clustering [39-41]. Some approaches to calculate initial centers for k-Means clustering exist in the literature [42, 43]. Zalik [44] introduced an extension of k-Means to perform clustering without pre-assigning the correct number of clusters. Some authors in [45] proposed an ACO based algorithm for data clustering and found encouraging results. A large number of approaches based on PSO algorithm have been developed for data clustering [46-50].

Although the above approaches solve the problems of k-Means up to some extent but they also encounter some drawbacks. Genetic algorithms suffer from expensive evolutionary operators and costly fitness function. Simulated annealing suffers from slow convergence speed and non-availability of computation function for stopping criteria. Limitations of tabu search include requirement of external memory and slowness in finding optimal solutions. ACO suffers from possibility of falling in local optimal solutions and tendency to stagnancy. Some of the limitations in PSO are premature convergence on early suboptimal solutions and poor results in complex data set [51-53].

In the past, several new intelligent approaches simulating the behaviour of swarm systems have been proposed. Artificial Bee Colony is a population-based algorithm introduced by Karaboga [13], which is inspired by the intelligent foraging behaviour of honeybees. ABC has been successfully used in wide applications such as neural networks, sensor networks, protein structure, image processing, data mining, industrial engineering, mechanical engineering, civil engineering and electrical engineering [54-57]. Solution to complex transportation problems as well as deterministic combinatorial problems in dynamic environments is made possible by intelligent features of bee swarm such as autonomy, self organizing, distributed functioning, division of labour, etc., [58-60].

There have been several surveys of ABC available in the literature. Karaboga et al. [61] have presented a comprehensive survey of ABC in terms of modifications, hybrid models and applications in various fields. In [62] the survey has given general features of ABC and comparative analysis of its application in different areas. The survey in [63] highlights the importance of ABC, its hybrid approaches and applications in wide areas. Kumar and Kumar [64] have presented modifications of ABC to solve a variety of problems and applications in selected areas. However, the present survey provides the comprehensive insight about the variants of ABC as well as its applications in solving data clustering problems.

2. Artificial bee colony algorithm

Honeybees perform a number of complex tasks in systematic manner, best example is collection of nectar and its processing [65]. The information about quality of food sources is shared among its colony members by means of dance language that acts as a communication behaviour [66]. The foraging range with proper precision allows a colony to exploit potential food sources with great efficiency and helps to concentrate its foraging on best patches [67]. Food transmission is the most effective way of communication in honeybee colonies and determines the requirements of the colony. Such requirements and the age of individual bees determine the division of labour in honeybees and thus their social life [68]. Study in [69] proves that the colony acts as a unit and among its members so that there is mutual dependence on each other. Their behaviour is closely related to the needs of the colony. A mathematical model developed in [70] enables a forager to adopt cooperative or direct recruitment of food sources. The effectiveness and simplicity of the whole process is possible because of the decentralized decision-making approach [71] and systematic mechanism of self-organization in honeybee colonies [72]. The honeybee swarm has a specific physical structure and not just a random collection of individuals [73].

Self-organization, a key feature of swarm system represents the emergence of complex collective behaviour from local interactions among agents exhibiting simple behaviours [74]. More interesting is that the resulting behaviour emerges without any control hierarchy, but with the autonomous functioning of individuals [72]. Another important feature of swarm is division of labour, a process in which specialized agents perform simultaneous activities resulting in performance that is more efficient as well as saving of time [6, 75]. The ratios of individual agents performing various activities are adjusted in order to respond to internal and external changes. This behavioural flexibility of individual agents is termed as plasticity, a key aspect of division of labour [76].

ABC is one of the widely studied algorithms, which is continuously inspiring researchers to apply in solving several real world problems. There are three groups of artificial bees in ABC: employed bees, onlooker bees and scout bees. Bees going to a food source already visited by them are employed while the bees looking for a food source are unemployed. Scout bees carry out search for new food sources, onlooker bees wait for information about food sources given by the employed bees through waggle dance. It means that number of employed bees are same as number of food sources. An employed bee becomes scout when the position of a food source does not improve through the predetermined number of attempts called “limit”. In this way, exploitation process is performed by employed and onlooker bees whereas scouts perform exploration of solutions. The details of ABC algorithm are given as under:

- Initialization phase

The locations of food sources are randomly initialized within the range of boundaries according to the equation

$$x_{ij} = x_j^{\min} + \mathrm{rand}(0,1)\left(x_j^{\max} - x_j^{\min}\right), \tag{2}$$

where $i = 1, \ldots, \mathrm{SN}$ and $j = 1, \ldots, D$. SN indicates the number of food sources and taken as half of the bee colony, D is dimension of the problem, x_{ij} represents the parameter for i-th employed bee on j-th dimension, $x_j^{\max}$ and $x_j^{\min}$ are upper and lower bounds of x_{ij}.

- Employed bee phase

Each employee bee is assigned to the food source for further exploitation. The resulting food source is generated according to the equation

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

where: k is a neighbour of i, $i \neq k$; φ is a random number in the range [–1, 1] to control the production of neighbour solutions around x_{ij}; v_{ij} is the new solution for x_{ij}. The fitness of new food source is now calculated using the equation

$$\mathrm{fit}_i = \begin{cases} \dfrac{1}{1+f_i}, & f_i \geq 0, \\ 1 + \mathrm{abs}(f_i), & f_i < 0, \end{cases} \tag{4}$$

where f_i is the objection function associated with each food source, and fit_i is the fitness value. A greedy selection is performed on x_{ij} and v_{ij}, i.e., original and new food sources to choose better one according to its fitness value.

- Probabilistic selection phase

For each food source, a probability value is calculated using the next equation, and an onlooker bee selects the food source according to this value:

$$p_i = \frac{\mathrm{fit}_i}{\sum_{j=1}^{N} \mathrm{fit}_j}, \tag{5}$$

where fit_i is the fitness value of i-th solution and p_i is the selection probability of i-th solution.

- Onlooker bee phase

The employed bees share the information about food sources with the onlooker bees for further processing. Each onlooker bee selects a food source to exploit according to the probability associated with it (i.e., more fitness, higher the probability). The chosen food sources are exploited for better solutions using Equation (3) and their fitness values are calculated using Equation (4). A greedy selection is again applied on the original as well as new food sources, similar to employed bee phase.

- Scout bee phase

If a food source does not produce better solutions even up to a predefined limit, the food source is abandoned and the corresponding bee becomes a scout bee. A new food source is randomly generated in the search space using Equation (2).

The employed, onlooker, scout bee phases and probabilistic selection phase will execute until termination criterion is satisfied. The best food source solution is obtained as output.

3. ABC variants

Karaboga [13] invented ABC algorithm based on intelligent foraging behaviour of honeybee swarm and the same was applied for solving unconstrained optimization problems in [77]. The authors in [78] tested the algorithm for multivariable function optimization and comparison was made with some popular methods such as GA, PSO and PS-EA. The results prove the better performance of ABC in comparison to other approaches. Karaboga and Basturk [79] successfully applied ABC in solving a set of constrained optimization problems. Karaboga, Akay and Ozturk [80] successfully applied the ABC algorithm to train neural networks and compared its performance with the genetic algorithm and back propagation algorithm. Karaboga and Basturk [81] compared the performance of ABC with algorithm like DE, PSO and EA and concluded that ABC is efficient to solve multimodal and multi-dimensional numeric problems. The study also pointed the colony size of 50-100 to provide reasonable convergence speed and moderate value of limit L for the scouts. A study on performance of ABC in solving multimodal and multidimensional optimization problems was made in [82] and compared with DE, ES, GA and PSO algorithms on a set of test functions. Since its inception, several variants of ABC have been developed to overcome its shortcomings and improve the performance. Some of these variants contain modifications of the original ABC while others contain hybridization of ABC with traditional and evolutionary algorithms. An Improved ABC algorithm proposed by Liu et al. [83] employed chaotic mapping having sufficient population randomness and improved ergodicity during initialization. The improved search equation in scout bee phase provided better convergence. One of the variants, gbest-guided ABC (GABC) algorithm improves the exploitation of ABC by applying global Best solution (gBest) inspired by PSO. The gbest term introduced in the solution search equation of ABC enhances the exploitation while maintaining the balance between exploration and exploitation of solution space. The algorithm was found superior on most benchmark functions [84]. The algorithm was further modified by adopting the information of both global best and best between current and random bee solution [85]. Taking inspiration from the global best ABC algorithms, El-Abd [86] modified ABC in grouping of bees into different sub-populations and use of local best information for update of search equations.

Fister et al. [87] introduced new crossover operator and mutation techniques in ABC to enhance performance. They also proposed to hybridize ABC with Nelder-Mead algorithm and RWDE method to enhance exploration and exploitation capabilities. Bansal et al. [88] proposed a new version of ABC namely Memetic ABC by adding an additional search phase to improve the exploitation process. The proposed phase makes use of one specific method called GSS approach to exploit the solution space in the neighbourhood of best solutions.

Kumar, Sharma and Kumari [89] introduced two new parameters in the memetic search phase to improve the local search process. The proposed RMABC algorithm makes use of Golden Section Search method and new parameters to search best solutions. Kojima, Nakano and Miyauchi [90] modified ABC by eliminating the use of scout bee phase and improving employed bee as well as onlooker bee phases in such a way to maintain balance between solution search speed and speed of convergence. The algorithm was successfully tested in dynamic optimization problems. Yu, Zhang and Chen [91] introduced a new position update strategy for onlooker bees to improve the exploitation process and enhance the convergence. The technique incorporates the good solutions as opposed to random solutions in position update of onlooker bees and at the same time adjusting the greediness degree using a control scheme.

In order to solve the real world constrained optimization problems, Brajevic and Tuba [92] developed a new UABC algorithm by enhancing the exploitation in onlooker bees and exploration in scout bees to maintain the balance. The algorithm proved its effective and robust performance in solving constrained engineering problems. Karaboga and Akay [93] modified ABC algorithm by incorporating Deb's heuristic rules and probability selection scheme for constrained optimization problems. Li and Yin [94] modified ABC for constrained optimization problems in such a way that employed bees generate solutions based on feasible rule method, whereas onlooker bees perform search in accordance with multi-objective optimization method. Akay and Karaboga [95] modified the ABC algorithm by incorporating Deb's three heuristic rules to make the feasible search. The resulting improved exploration and exploitation capability of ABC algorithm prove better performance as compared to DE and PSO algorithms on large scale unconstrained optimization problems.

Some researchers also modified ABC algorithm to solve binary optimization problems. Kashan, Nahavandi and Kashan [96] introduced DisABC, a modified version of ABC for binary optimization problems. The algorithm makes use of a differential expression employing dissimilarity measure between binary structures and successfully applied on UFLP problem. Pampara and Engelbrecht [97] presented three versions of ABC for binary-valued optimization problems and found the performance of angle modulated ABC better than normalized and binary ABC. Chandrasekaran et al. [98] developed two variants of ABC namely binary coded ABC and real coded ABC to solve the unit commitment and economic dispatch problem. Kim et al. [99] proposed binary ABC algorithm for job scheduling problems. They introduced efficient BABC by use of flexible ranking strategy for selection of jobs in order to maintain exploration and exploitation of the search solutions.

Singh [100] successfully implemented ABC algorithm for the leaf-constrained minimum spanning tree problem, which is a discrete optimization problem. Pan et al. [101] proposed a discrete version of ABC to solve flow shop scheduling problems. The problems were solved by utilising the effective population initialization approach and self-adaptive neighbouring food source generation strategy of ABC. Yurtkuran and Emel [102] modified ABC for use in solving a combinatorial problem such as p-center problem. In this process, solutions are represented using random key-based encoding and different search techniques are employed in search process to generate new solutions. Li, Pan and Gao [103] developed a Pareto-based discrete ABC (P-DABC) algorithm by combining the discrete version of ABC and an external pare to archive set to solve multi-objective flexible job shop scheduling problems. In the proposed algorithm, the food source is represented by two components: routing component and scheduling component. One crossover operator is employed for effective sharing of information in routing component.

Beloufa and Chikh [104] modified ABC to enhance the exploration and exploitation processes of employed or onlooker bees by employing a blended crossover operator. The modified algorithm was used to create an effective fuzzy classifier and successfully applied in diagnosis of diabetes disease. Khorsandi, Hosseinian and Ghazanfari [105] modified the search equation in original ABC to improve the exploration and exploitation process while solving optimal power flow problem using fuzzy based method.

Diwold et al. [106] proposed two variants called ABC_{gBest} and $ABC_{gBestDist}$ to study the selection of reference locations that may affect the position of artificial bees. They also studied the influence of population size, ratio of employed and onlooker bees in ABC optimization. The variants make use of global best reference and distance based reference to generate new solutions. Another variant, Hybrid Differential ABC (HDABC) presents combination of ABCA with Differential Evolution strategy. The algorithm was tested on various benchmark functions and proved efficiency in terms of better convergence and quality of solutions [107]. Some authors in [108] proposed Enhanced ABC (EABC) algorithm incorporating two modifications to enhance the neighbourhood searching as well as new-food-source inducting performance of ABC. The algorithm was tested and provided better performance. An enhanced global-best ABC optimization algorithm (EBABC) invented by Abro and Mohamad-Saleh [109] takes into consideration self-reinforcement, positive and negative feedback through mutation equations. EBABC was compared with several algorithms and proved better performance.

Li, Niu and Xiao [110] proposed a hybrid algorithm called PS-ABC algorithm that is having the concept of prediction and selection. The algorithm incorporates the features of three variants of ABC, i.e., basic ABC, GABC and I-ABC to solve optimization problems. I-ABC algorithm improves the exploitation capability of basic ABC by introducing inertia weight and acceleration coefficients in the search process. PS-ABC makes use of three solution search equations to improve the search process as well as convergence speed and generate the best solution. The shortcomings of PS-ABC algorithm such as premature convergence and slower convergence were removed in Enhanced Probability Selection Artificial Bee Colony algorithm (EPS-ABC) developed by Abro and Mohamad-Saleh [111]. The algorithm employs the modified equations to enhance exploration and avoid local optima traps. The intelligent scout bee stage of PS-ABC helps to find the optimal solutions. Main idea introduced in the algorithm is to generate solutions around random picked food source and gbest food source in addition to the current food source. Sharma, Bansal and Arya [112] proposed three modifications in the basic ABC by incorporating levy flight local search strategy, opposition based learning method and a position update equation to guide the search process. The local search method improves the exploitation capability by recalculating the step size while opposition based learning enhances the convergence speed. The performance of ABC was improved by use of NABC algorithm proposed by Xu, Fan and Yuan [113]. NABC employed the hybridization of DE/best/1 scheme and ABC with a solution pool having best solutions. The solution pool provided the scope for the bees to search the neighbourhood of different best solutions and not just global best solution. Kang, Li and Li [114] proposed a memetic algorithm by combining ABC with Hooke-Jeeves pattern search method for global optimization problems. The algorithm employed ABC to explore regions of attraction and pattern search method to exploit the regions for best solution.

Tsai et al. [115] proposed Interactive ABC algorithm and improved the exploration capability of ABC algorithm by applying the law of universal gravitation in onlooker bees. Alatas [116] improved the convergence speed and avoided local optima traps in ABC by using sequences from chaotic number generators in place of random numbers. Chaotic sequences are deterministic in nature and possess spread-spectrum characteristics. Kiran and Gunduz [117] modified ABC algorithm by inserting crossover operation on certain employed bees with good solutions to generate neighbour for onlooker bees. The modified algorithm namely CABC was applied to solve energy demand problem and provided better convergence. Dongli et al. [118] proposed two modified ABC algorithms to improve the global exploration capability and convergence speed. In first algorithm, search range is made wider for improved exploration of employed bees while in second, sensibility replaced random number in searching of onlooker bees. In order to widen the search space to generate new solutions, some authors in Dongli et al. [119] introduced the concept of multi-exchange neighbourhood resulting in improved global search and better convergence. Banharnsakun, Achalakul and Sirinaovakul [120] proposed a best-so-far ABC algorithm by introducing three major changes such as best-so-far method for the onlooker bees, adjustable search radius for scout bees and objective-value-based comparison of new solution with old solution to generate better solutions with fast convergence.

One improved version of ABC was proposed by Gao and Liu [121] to provide stability, accuracy and robustness. The IABC algorithm employed new initialization approach based on chaotic systems and opposition-based learning method. The algorithm also employed two new solution search equations for better convergence and population diversity. The algorithm was modified by presenting a new algorithm namely ABC/best in which two solution search equations were replaced in order to improve the exploitation process [122]. The focus of algorithm was on the search around best solution of the previous iteration. Gao and Liu [123] developed MABC by employing an initialization approach based on chaotic systems and opposition learning methods for better convergence. In addition, a modified search equation is also induced to enhance exploitation capability. To overcome the issue of poor exploitation in ABC, Gao, Liu and Huang [124] introduced a modified search equation to develop CABC. The convergence was enhanced by employing orthogonal learning strategy in CABC. Sharma and Pant [125] developed I-ABC and I-ABC greedy algorithms to find the optimal solutions using ABC, where the initial food sources are generated by use of opposition based learning method. I-ABC greedy makes use of greedy bee concept to find the best solution and enhanced convergence. Xiang and An [126] added four modifications to the basic ABC in order to enhance convergence performance, population diversity, exploration capability and avoiding local minima traps. The modifications such as chaotic initialization, roulette wheel based reverse selection, modified search equation and chaotic search make the ERABC as efficient and robust optimization algorithm.

Bansal et al. [127] introduced a new control parameter namely cognitive learning factor and modified the range of existing control parameter in ABC to propose BABC algorithm. The above modifications help to maintain the balance between exploration and exploitation capabilities of ABC. Biswas et al. [128] proposed a modified algorithm MiMSABC to ensure effective exploration and exploitation in multi-swarm populations. Initially groups of foragers having their perturbation schemes were taken. In order to enhance the performance and better exchange of information, rank based migration scheme was used in the algorithm. Luo, Wang and Xiao [129] proposed a new algorithm COABC by introducing a new search equation to improve the exploitation process in onlooker stage. The update process in onlooker phase employed the global best solution to find new candidate solutions. Sulaiman, Saleh and Abro [130] proposed a new version of ABC to enhance the fitness of poor solutions by using a modified mutation scheme. This way, the fitness of every possible solution is increased and provided faster convergence and avoidance of premature convergence. Gao, Liu and Huang [131] introduced a new search equation in onlooker bees phase of ABC to improve the search process. A local search algorithm called Powell's method is also incorporated in the hybrid algorithm to improve the exploitation ability. Das and Chaudhur [132] presented hybridization of modified Quadratic Approximation with slight change in scout bees activities of ABC and generated better results.

Akay and Karaboga [133] proposed a modified ABC algorithm that studied the effect of various parameters such as perturbation rate, limit and scaling factor while solving real parameter optimization problems. In addition to the single parameter called limit being used in basic ABC algorithm, the modified algorithm introduced an additional parameter (i.e., modification rate) to control the frequency of perturbation. Another parameter to control the magnitude of perturbation is scaling factor. The modified algorithm performed better on hybrid functions as compared to PSO, DE and ES algorithms. Alizadegan, Asady and Ahmadpour [134] proposed two modified ABC algorithms. In the first one, they used different ratios of employed and onlooker bees. The results prove the better performance of ABC having more onlooker bees. The second algorithm employed the changes of dimension's value during each iteration and generated positive results. Liang, Liu and Zhang [135] introduced the dynamic grouping strategy using cooperative coevolving to solve large-scale optimization problems. The main concept to generate better candidate solutions was mutual learning as well as global best positioning. Aydin et al. [136] developed a new version of ABC called IABC-LS to enhance the intensification ability and better convergence. The local search procedure in the algorithm helped to find better solutions and provided better performance.

Since ABC is efficient in solving single objective problems, it has also been successfully applied in multi-objective optimization problems. This was made possible due to many characteristics of ABC such as use of less control parameters, absence of gradient-based information and well balancing of exploration and exploitation capabilities. Vector Evaluated Artificial Bee Colony (VEABC) algorithm for multi-objective optimization is based on concept of VEGA and VEPSO algorithms. The optimal solution is generated as the communication of information takes place between separate swarms employed for multiple objectives [137]. Hedayatzadeh et al. [138] presented a Multi-Objective Artificial Bee Colony (MOABC) algorithm to solve multiple objective problems. The method makes use of intelligent foraging by various bee types and utilizes the information supplied by an external archive to maintain the good solutions. A multi-objective artificial bee colony algorithm for optimization of power and heating system was proposed by Atashkari et al. [139]. Zou et al. [140] proposed multi-objective variant of ABC algorithm by making use of pareto concept and maintaining non-dominated solutions in an external archive. The algorithm does not employ employed bees or scouts and all bees are considered as onlooker bees. Arsuaga-Rios, Vega-Rodriguez and Prieto-Castrillo [141] extended ABC algorithm to solve job scheduling problem with focus on two objectives namely cost requirements and optimizing time. Akbari et al. [142] modified the MOABC algorithm by using a grid to control diversity over the fixed-size archive. Special features of the modified algorithm such as effective trajectory adjusting and maintaining the diversity guide pave the way to solve the multi-objective problems in better way. Abedinia and Barazandeh [143] proposed IABC algorithm for application in distributed generation, network planning and evaluation of load demand. Yahya and Saka [144] combined MOABC algorithm with Levy flights walks by employed bees to solve a non-linear CSLP problem. The resulting hybrid algorithm improves the balance of search processes of employed bees and onlooker bees.

Li and Yin [145] developed a hybrid algorithm for estimation of parameters in chaotic systems. The algorithm introduced a hybrid bee operator to integrate the exploration ability of DE with exploitation capability of ABC. In [146] the authors modified the employed bee phase of ABC by using best solutions as well as random numbers in local and global neighbourhoods thus providing balanced exploration and exploitation. Shah et al. [147] presented a hybrid ABC by incorporating the global best solution in solution search equation of employed and onlooker bees phase. The scout bee phase was also modified by including the best-guided strategy. Bansal et al. [148] proposed three modifications in ABC: Self-adaptive step size in employed bee phase, updates in two components with modified step size in onlooker bee phase, limit parameter based on fitness of solutions in scout bee phase. Yazdani and Meybodi [149] modified the neighbour search process of employed and onlooker bees by use of roulette wheel selection and a random number of dimensions in choosing targets. A new scout mechanism was also provided for improved diversity and local optima avoidance. Liang and Lee [150] proposed a modified artificial bee colony algorithm by employing several strategies such as solution sharing, instant update strategy, cooperative strategy, and population management. Huang, Wang and Yang [151] introduced a new search equation based on the combination of elite solution pool strategy and block perturbation strategy for employed bees and another search equation based on the best solution of current swarm for onlooker bees. Some authors in [152] performed experiments on benchmark functions using different selection schemes of ABC and found encouraging results. An improved artificial bee colony algorithm for constrained optimization problems is proposed in [153]. The algorithm involves the use of rank selection mechanism for exploitation of food sources by onlooker bees. The algorithm proposes a new search mechanism by use of best-so-far solution, in addition to use of periodic boundary handling mode to maintain the population diversity.

4. ABC applications in data clustering

The ABC algorithm to solve clustering problems was developed by Zhang, Ouyang and Ning [154] that adopted Deb's method instead of greedy selection process to tackle infeasible solutions. The method involves use of a tournament selection operator to compare two solutions in accordance with three heuristic rules [155]. The algorithm adopts the Forgy algorithm to assign data points to the clusters and updating of cluster centers. In this process, cluster centers are updated when all data points are assigned to the closest cluster centers [156]. Karaboga and Ozturk [157] applied ABC in data clustering for classification purpose and compared its performance with PSO and other algorithms. The algorithm produced successful clustering results in comparison to other techniques. Zou et al. [158] modified the ABC by employing the cooperative strategy to find best solution with contribution of every individual. The final solutions are obtained in accordance with information from all individuals. Zhang et al. [159] proposed Chaotic ABC, a modified version of ABC to solve partitional clustering problems. In the algorithm, Rossler chaotic number generator was incorporated during initialization of parameters to ensure more robustness and better quality of solutions.

Saeedi, Samadzadegan and El-Sheimy [160] successfully applied ABC in finding optimal clusters during object extraction from multi dimensional LIght Detection And Ranging (LIDAR) data that is used in 3D modelling of urban areas. Abdulsalam and Bakar [161] modified ABC to detect cluster-based deviations that constitute important application domains. The process is completed in two stages and deviations are detected in terms of outlier factor values for each object. Banharnsakun, Sirinaovakul and Achalakul [162] added the concept of multiple patrilines in best-so-far ABC algorithm to improve the quality of solutions as well as computation speed. The patrilines introduced the distributed approach idea in the search space and hence the parallel execution across multiple units for effective exploration. Ju and Xu [163] applied ABC in k-Means clustering to overcome the local optimal problems and produce effective clusters. Finally, a recommendation list for the target users is generated using modified collaborative recommendation approach. Lei, Huang and Zhang [164] presented a modified version of ABC for data clustering problem. Inspired by the strategy of PSO, they introduced additional parameters in ABC for effective search process and enhanced accuracy. The algorithm was found efficient in clustering analysis of data about DNA microarray gene expression and data sets on Protein-Protein Interaction (PPI). Wu, Lei and Tian [165] applied ABC in proposing a new clustering method for PPI networks. The ABC helps in optimizing the search process of original functional flow model and obtains better clustering results.

Marinakis, Marinaki and Matsatsinis [166] developed a two-phase Discrete ABC-GRASP algorithm that performs the task of feature selection in first phase using discrete ABC. In the second phase GRASP, an iterative search algorithm is utilized to solve the clustering problem.

Karaboga and Ozturk [167] applied ABC in fuzzy clustering. Various tests performed on medical data proved the successful performance of ABC algorithm. Lei, Tian and Wu [168] proposed a new clustering model for PPI networks by use of ABC search mechanism to find the cluster centers and then performing clustering through Intuitionistic Fuzzy Clustering (IFC) method. Su et al. [169] introduced some modifications in ABC such as variable length strings, mutation operations and scheme for candidate solutions to generate Variable string length ABC (VABC) algorithm. The proposed algorithm in combination with Fuzzy C-Means was used to find fuzzy partitions with accuracy and proper convergence. Yanto et al. [170] modified the ABC algorithm to find the objective function of Fuzzy K-Partition objective function. The hybrid algorithm was implemented on categorical data sets and obtained better dunn index values.

Dilmac and Korurek [171] proposed a classifier called MABCC based on modified ABC and applied in ECG signal analysis. The classifier generated satisfactory results when compared with GA and PSO based classifiers. Hsieh and Yeh [172] developed a Grid Scheme-Least Squares Support Vector Machine (GS-LSSVM) learning paradigm for classification problems by integrating grid scheme into least squares support vector machine. The ABC algorithm is employed to optimize parameters and improve classification. Shukran et al. [173] modified ABC for use in classification rule mining having six components. The algorithm proved its performance during testing on UCI datasets and comparison with other classification algorithms. Schiezaro and Pedrini [174] applied ABC in UCI data sets for feature selection and proved superior classification accuracy in selected features for majority of the data sets.

Krishnamoorthi and Natarajan [175] proposed two modifications on ABC for clustering problems. In the first algorithm, they introduced k-mean operator in scout bee phase for better performance; in the second algorithm, FCM operator generates new solutions in scout bee phase based on employed bee and onlooker bee phases. Lee, Cheng and Jiang [176] developed an early-warning model for business prediction and successfully applied ABC based clustering in the prediction of business failure. The tests performed on data of listed companies prove the accuracy of proposed model. Rakshit et al. [177] proposed ABC based clustering technique in improving the accuracy by reducing the redundancy in feature set. The results prove that ABC helps to enhance the accuracy by reducing the number of redundant features in the data set. Bharti and Singh [178] improved the exploitation ability by embedding chaotic local search and gradient search methods in ABC. The solution search equation was also improved in employed and onlooker phase to generate global best solution. The modified algorithm generated better quality of solutions and enhanced convergence speed on three text datasets.

Sridhar et al. [179] integrated the concept of rule-based system in ABC to develop an online application for diagnosis in chilli plants. The two-stage expert system produced better and efficient solutions. Shanthi and Amalraj [180] proposed a hybrid approach with combination of ABC and Harmonic Search algorithms. The modified C-ABC algorithm is able to find the local optimal solutions and has been used to develop a new clustering method for neural networks. The tests proved its performance in terms of better convergence, enhanced exploration and avoiding local optima traps. Yan et al. [181] developed a new version of ABC called Hybrid ABC algorithm for clustering by adding the crossover operator of GA to enhance the information exchange between bees and the searching ability of ABC. The results prove the better convergence speed and accuracy as compared to other algorithms. Uzer, Yilmaz and Inan [182] applied ABC for reducing the feature vector dimensions in a hybrid method and then applying support vector machine classifier on the selected data. The approach was successfully applied in diagnosis of liver and diabetes. Tan et al. [183] modified ABC by introducing a key initialization method to generate the initial cluster centers by the reference of former ones. The modified algorithm is able to enhance the quality of clustering in addition to reducing the latency. Ji et al. [184] introduced ABC-K-Modes clustering algorithm for categorical data by use of traditional k-modes method. One-step k-modes procedure was used for solution search in employed and onlooker phase. The multi-source search technique was adopted for scout bees to accelerate the convergence of algorithm. Chaurasia and Singh [185] presented a hybrid artificial bee colony algorithm to solve the registration area-planning problem. The algorithm manages to preserve the grouping property of the problem while generating new solutions. Venkatesh and Singh [186] proposed two ABC versions for the multiple traveling salesperson problem with a single depot. The problem was evaluated using two different objective functions i.e. minimizing total distance travelled by all the salespersons and minimizing the maximum distance travelled by any salesperson. Sundar and Singh [187] developed a grouping based ABC algorithm to solve Blockmodel Problem. The proposed algorithm is able to preserve the grouping information as far as possible.

Reisi, Moradi and Abdollahpouri [188] proposed a feature weighting based ABC algorithm for data clustering. The modified method involves the use of different weights to each feature during initialization phase to produce good clustering results. Alshamiri, Singh and Surampudi [189] hybridized the Extreme Learning Machine (ELM) approach in ABC algorithm in order to improve the quality of clustering. The ELM is used to increase the separability of the input data into a high-dimensional ELM feature space by way of nonlinear transformation and ABC is then applied to perform clustering within this feature space. To solve the clustering problems more effectively and efficiently, improvements in three phases of original ABC were reported in [190]. The proposed algorithm produced better results by incorporating K-Means algorithm in initialization phase, an improved search equation in onlooker bees phase, Hooke and Jeeves-based method in scout bees phase. The authors in [191] developed a hybrid ABC algorithm to enhance the exploitation as well as convergence speed of original ABC. The proposed algorithm employs a modified initialization phase in order to generate better initial solutions. The onlooker bees phase is also modified by incorporating the variable tournament selection in place of mechanism of roulette wheel selection. The hybrid algorithm performs better on various indices and provides optimal clustering solutions on standard data sets.

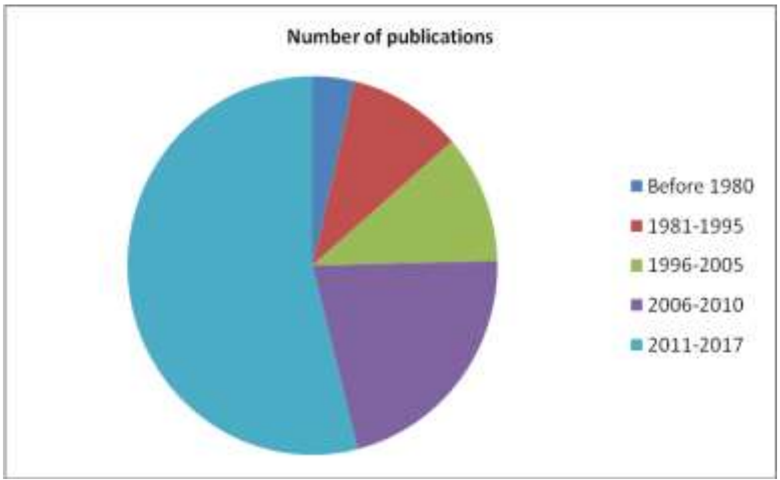

Fig. 1. Distribution of publications in the survey

5. Conclusion

This paper presents a review of previous research related to artificial bee colony algorithm, ABC variants and applications in data clustering. ABC is a simple and flexible algorithm and requires less parameters to be tuned in comparison to other meta-heuristic algorithms. It has become clear that original ABC, its modifications, as well as hybrid algorithms are capable to solve a wide range of optimization problems including continuous, combinatorial, constrained, binary, multi-objective, and chaotic, etc. Various experiments performed in the relevant literature prove the efficiency, accuracy and effectiveness of ABC in solving several optimization problems.

ABC algorithms have been successfully implemented for data clustering problems and gave wonderful results leading to better prediction and analysis of data. In total, 191 papers have been reviewed, in which the concepts of swarm intelligence techniques are mentioned, and particular ABC. It may be seen that the number of papers related to applications of ABC are increasing year by year. We hope that this survey will be very helpful for the researchers who are working in the area of ABC and data clustering. As seen from the studies given in the paper, more research is still required on ABC to overcome its limitations; development of new strategies is still required for generation and distribution of good solutions, faster convergence and improved exploitation for making ABC ideal in solving complex real world problems.

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