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Artificial Bee Colony for Optimization of Process Parameters for Various Enzyme Productions

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CONTENTS

9.1 Introduction

Optimization is the essential and crucial part of many optimization processes of designing, whether it is designed for business planning or machine learning. The optimization purpose could be anything; it is used to minimize the consumption of energy, time of the experiments, waste, costs, and other

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environmental impacts (pH, Temperature, agitation speed, etc.) or to maximize the response, i.e., performance, profit, efficiency, and sustainability of work. In real-world applications, there is limited time and money; so for this, there are many solutions to overcome this problem. One of them is experimental designing, which is subject to a wide range of complex constraints (Tsai et al. 2009). To solve these problems, optimization techniques are needed. As in reissue problems, most issues are in nonlinear terms for objective functions, so there is a need to use these essential sophisticated tools for the optimization that deals with such types of problems. Accumulation and the estimation purposes of this objective are further time-consuming processes – the major problem in designing fields. Therefore, among all the naturally inspired algorithms, Artificial Bee Colony Optimization (ABC) is the most common swarm intelligence (Karaboga and Basturk 2007) inspired by a field of biological computing that applies concepts from the combined behavior of swarms (i.e., bees) to solve problems in different areas like optimization of process parameters, etc. The researchers have been attracted to the combined quick performance of bees in these algorithms. The cumulative behavior of these bees is called swarm behavior. Entomologists study the engineer's and the biological swarm's behavior and apply these models to the framework toward complex problems. Swarm intelligence is artificial intelligence that mainly deals with the collective behavior of swarms by interactions with individuals without any supervision. Any effort to algorithm design before distributing this is used for the solution to the problem of social animals (Zhu and Kwong 2010). The swarm intelligence's main advantage is scalability, tolerance of the fault, speed, adaptation, and parallelism. Labor division and self-organization are the two critical parameters of swarm intelligence. Encountered units of local stimuli may respond individually in a self-organizing system and globally accomplish charge via labor separation without centralized supervision. The whole arrangement should have the ability to adapt to inner and outer changes capably. Four basic properties have been characterized on which self-organization mainly depends: positive feedback, negative feedback, multiple interactions, and fluctuations (Mohapatra et al. 2017). Positive feedback indicates that another individual by some instruction, like dancing bees, leads to another food source site. Negative feedback indicates exhaustion of the food source. Fluctuations refer to the random behaviors of each individual in the exploration of new sites (Beg et al. 2012). ABC may apply to various problems, including the training of artificial neural networks (ANN), for the designing of the infinite impulse response (IIR) (Zhang et al. 2010), for solving the problems related to constrained optimization (Sonmez 2011), and in the tertiary structure's prediction of proteins (Tsai et al. 2009). ABC algorithm performance toward the optimization of several other algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), Particle Swarm Inspired Evolutionary Algorithm (PS-EA), Differential Evolution (DE), and different evolutionary strategies (Liu et al. 2018). All the above-mentioned parameters have the ability to deal with specific kinds of clusters. However, there are many problems in this field that need to be solved (Chang and He 2014; Garoudja et al. 2015). First, deeper knowledge about the algorithms needs to understand the empirical sets. The performance of the algorithms mainly depends on the quality of the parameters significantly. Second, some codes can work fine with a limited kind of potential but not with others. Parameters are optimized for a high amount of enzyme production (Babaeizadeh and Ahmad 2014). Among all the different parameters for enzyme production, the condition at which the processes performed best should be optimized (Zhu and Kwong 2010). Usually, the process of higher enzyme production may be optimized using different variables, i.e., temperature, reaction time, pH, and nutrient concentration (Ilie and Bădică 2013). To achieve higher enzyme production, the optimization of the variables is generally not possible for "one variable at a time" approach (Baykaso et al. 2007). In biotechnological processes, researchers started statistical optimization and nature-based optimization approaches to increase the production of enzymes (Agrawal et al. 2016; Garlapati and Banerjee 2010; Liu and Tang 2018; Mahapatra et al. 2009). To support the facts mentioned earlier, research has to start utilizing the different natural development-based easy computing approaches to optimize enhanced enzyme production (El-Abd 2011). ABC is one of the optimization techniques that involves the bees for optimization purposes. ABC is applied to the broad area for optimization purposes. There are many reports published on ABC optimization from 2005 to 2022, as shown in Figure 9.1.

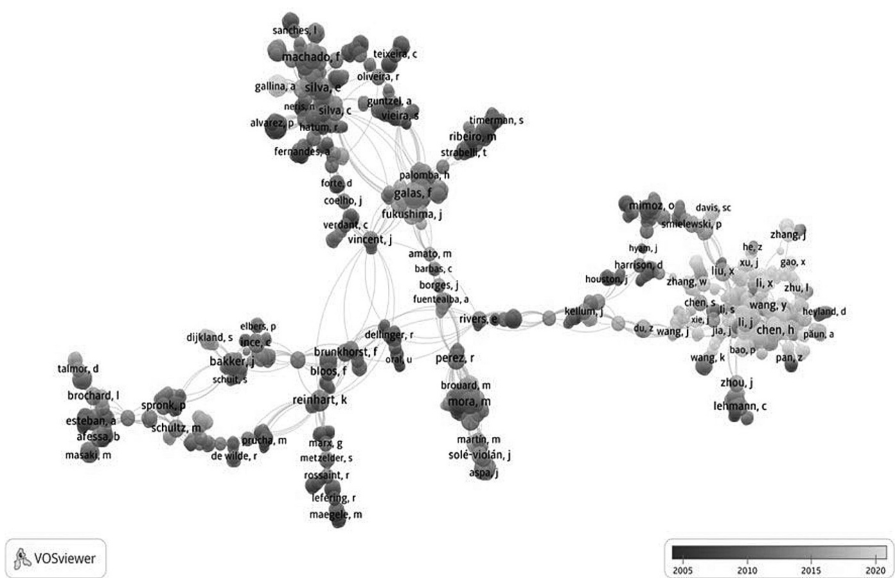

FIGURE 9.1
Publications related to ABC optimization from 2005 to 2021.

9.2 ABC Algorithm Motivations

ABC algorithms are commonly known swarm methods for optimization which is mainly inspired by bees foraging behavior (Karaboga et al. 2014). Throughout the process of optimization, the ABC algorithm is featured by local and global exploration (Li et al. 2015). However, the local accuracy search for the ABC is not very acceptable (Zhu and Kwong 2010), leading to a large number of remedies proposed for this imperfection. The most proposed ABC variants have been deemed for adjustment of the local utilization of the equations for the achievement of a good intensity search. For this, three major pathways were taken: (i) adoption of novel principle from the external world, (ii) integration of the ABC with the other metaheuristics, and (iii) adjustment of the self-adaptivity for the local search concentration (Gao et al. 2014). It is tough to analyze the outperformance of ABC due to its statistical significance in comparative numerical experiments (Xiang and An 2013). In-depth mathematical analysis in the research made these algorithms precious. The difference with the first two variation options – and that ABC variants are self-adaptive (i.e., third method) – are understandable intuitively (because of no involvement of outside-world, complicated principles), and continue the novel framework in the conventional algorithm.

9.3 Optimization of Artificial Bee Colony Algorithm

Honey bees can effectively determine the highest quality of food sources in nature. Hence, the intelligent foraging bee behavior is finding a good solution for solving optimization-related problems (Li et al. 2015; Sathesh Kumar and Hemalatha 2014; Sharma et al. 2021; Zhang et al. 2021). In general, for searching the food sources, the honey bees' colonies are mainly separated into three kinds, i.e., employed bees, onlooker bees, and scout bees (Figure 9.2). For the nectar source exploitation, the employed bees are responsible (Bansal et al. 2011). They go to the beforehand food source position and give the information to onlooker bees about the quality of the food source. Then, onlooker bees wait in the hive and decide to explore the information about food sources. For finding the new source of the nectar, scout bees search randomly in the environment either depending on the internal motivation, based on the possible clues externally (Hakli and Kiran 2020). The nectar position implies the possible solution for the optimization problems, and the profitability of the source of nectar corresponds to the possible solution for the quality. The respective employed bee should exploit the nectar source (Hu et al. 2021; Kasihmuddin et al. 2021; Gautam et al. 2019). The sources

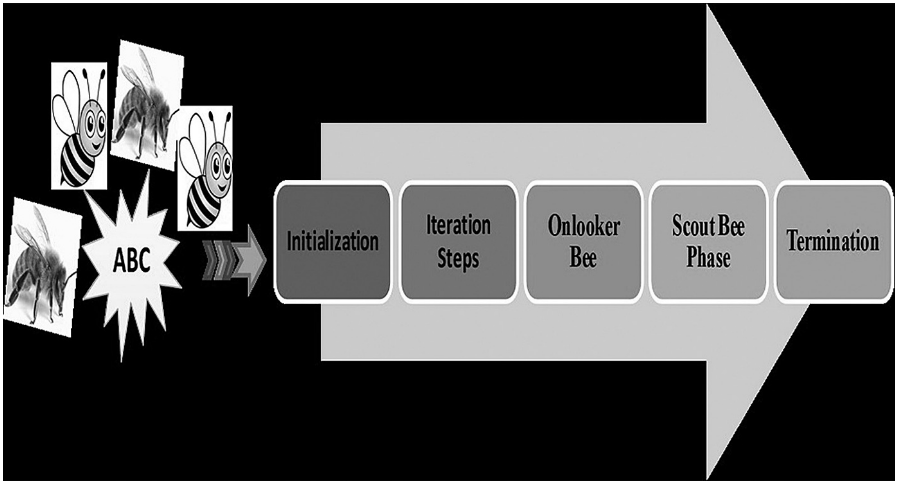

FIGURE 9.2
Honey bee colony according to the food source.

of nectar are equivalent to the number of employed bees and onlooker bees (Bansal et al. 2011). In this method, good solutions were obtained with employed bees and the spectator bees for the convergence improvement in the speed, and scout bees mainly improve the capacity to eliminate a local optimum (Babaoglu 2015).

9.4 Honey Bees' Foraging Behavior

Honey bee colonies can prey on a large number of food sources in a large field area and fly high up to 11 km to prey on the source of food. The employees in the colony are about an area of its members as collectors. Foraging processes is initiated by the search for a promising patch of the flower using scout bees (Brezočnik et al. 2018; Zhang et al. 2012). During harvest, the season colony maintains the percentage of scout bees. When bees identified the patch of the flower, they started looking for more with the hope of finding a better one. For the identification of better patches, the scout bees search randomly (Li et al. 2019; Harrison et al. 2018; Leu and Yeh 2012). Scout bees update their conspecifics resting in the hives for the quantification of the food source, which also includes the sugar content. Nectar was deposited by scout bees get on the "dance floor" in front of the hives and communication with the other bees was done by performing a type of dance known as "waggle dance" (Babaeizadeh and Ahmad 2014; Bansal et al. 2011; Chuang et al. 2008).

9.5 Iteration Steps in ABC for Optimization

The study of ABC follows mainly three most important steps (Akay and Karaboga 2012): (i) food source identification by employed bees; (ii) gathering the information about the source of food and choosing the quality of nectar – food source insurance is decided by onlooker bees, and employed bees gather the information and decide the eminence of nectar for scout bees, finding and making use of the ones in which they are interested; (iii) reach of food source. In the initial stage, the food source locality was selected randomly by bees and the qualities of their nectar were measured. Then, information about nectar sources is transferred by employed bees to onlooker bees which are waiting within beehives in the dance vicinity. After information distribution, every employed bee proceeds to the food source to check some stages in the previous cycle, when the food source position has been recalled along with information observed in the source of food. In the final stage, at the area of food source, the information from employed bees is retrieved by onlooker bees. Therefore, the information on food source quality in nectar is transferred through the employed bees. Then, the subsequent choice of other food sources mainly depends on the experiential information. Scout bees erratically generate a new source of food from deserted swap by onlooker bees.

9.5.1 Swarm Initialization

ABC algorithms have three major process parameters, i.e., the population which is generally a number of food sources, for the testing of subsequent food source numbers, they are mainly selected as deserted (limit), and criteria of termination, which mainly depend on the cycle numbers. Originally, Karaboga et al. (2014) demonstrated that the ABC number for a food source is equival to the number of employed and onlooker bees. In the beginning, it assumes a regularly distributed swarm source of food (SN), wherever each source of food x_i (where i = 1, 2, …, SN) is mainly a D-dimensional vector. A subsequent equation generally used for every source of food is shown in Equation (9.1):

$$x_{i,j} = x_j^{\min} + \varphi_{i,j}\left(x_j^{\max} + x_j^{\min}\right) \tag{9.1}$$

where $\varphi_{i,j}$ is random (0,1) real numbers for equal distribution and i = 1,2, …, SN, j = 1, …, D, and $x_j^{\max}$ and $x_j^{\min}$ are the dimensions for upper and lower bounds.

9.5.2 Onlooker Bee

Food source numbers designed for onlooker bees are like a food number for sourced employed bees. During this duration phase, all employed bees share new sources of food information about the availability with onlooker bees. Onlooker bees generally determine the probability of selection for every food source that is engendered by an employed bee (Gao et al. 2014). There are several schemes for calculating probability and they must include suitability. For each food source, the probability is usually based on its capability as shown in Equation (9.2):

$$P_i - = \frac{\text{fit}_i}{\sum_{i=1}^{SN} f_i t_i} \tag{9.2}$$

where fit_i is the value of fitness for the minimization solution problems.

9.5.3 Scout Bee Phase

Trials numbers are majorly related to every source of food which has not further been updated or improved. If the food source is not upgraded by predefined tries by employed and onlooker bees, then the food source is considered to be deserted and the employed bees associated with the food source are transformed into the scout bees and then the scout bees' phase is initialized. Then, the source of food is replaced and the scout bee finds a new source of food. An essential control parameter for the predefined cycle's number is called the limit for rejection at ABC (Banharnsakun et al. 2010). At this time, scout bees are inserted into a new source of food.

9.5.4 Termination

The extinction criterion of ABC is commonly founded on an advanced number of groups or maximum cycle number (MCN) (Rao et al. 2008). This cycle number is presented by the worker prior to the simulation of the ABC algorithm.

The foraging bee's behavior has mainly four characteristics that defines self-organization and rely upon the following expressions.

i. Positive feedback: If the nectar increases, the amount of food source increases, and visiting onlookers' bees can increase proportionally.
ii. Negative feedback: Poor food source process exploitation was stopped by the bees.

iii. Fluctuations: Scout bees can transport the search procedure randomly for identification of the new sources of food.

iv. Several interactions: Food sources information is transferred by employed bees with nestmates (onlookers) which are waiting in the area of dance. The above re-examination is explained by the bees' foraging behavior, which fully satisfied the principle defined by Millonas (1993).

9.6 ABC in Process Optimization Methodology

The methodology for ABC optimization is commonly dependent on the concept of simulating the foraging behaviors of bees in the natural environment (El-Abd 2011; Hakli and Kiran 2020). Bees are naturally around their hives, exchanging and communicating information with each other on sources of food to maintain the populated colony. The two main steps of bees categorized above performed different tasks to discover the best source of food to sustain their colony (Figure 9.3). Onlooker and employed bees developed the source of food in their local neighborhood. Then, bees searched for solutions for the deterministic selection of employed bees and probabilistic selection of onlooker bees. Scout bees randomly attempt for a new source of food search for exploring the new regions for search space. These simulated bees then fly

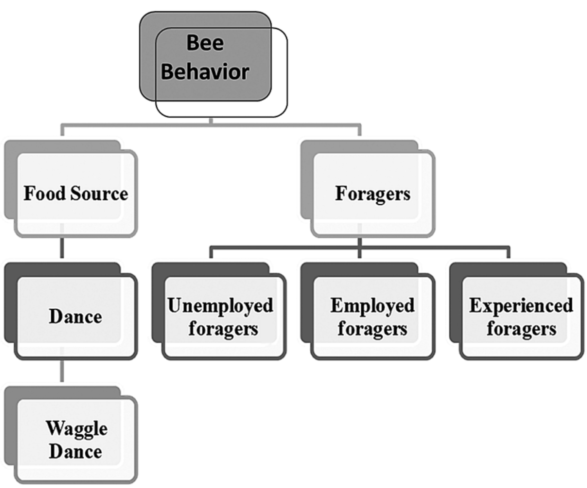

FIGURE 9.3
Steps involved in artificial bee colony methodology.

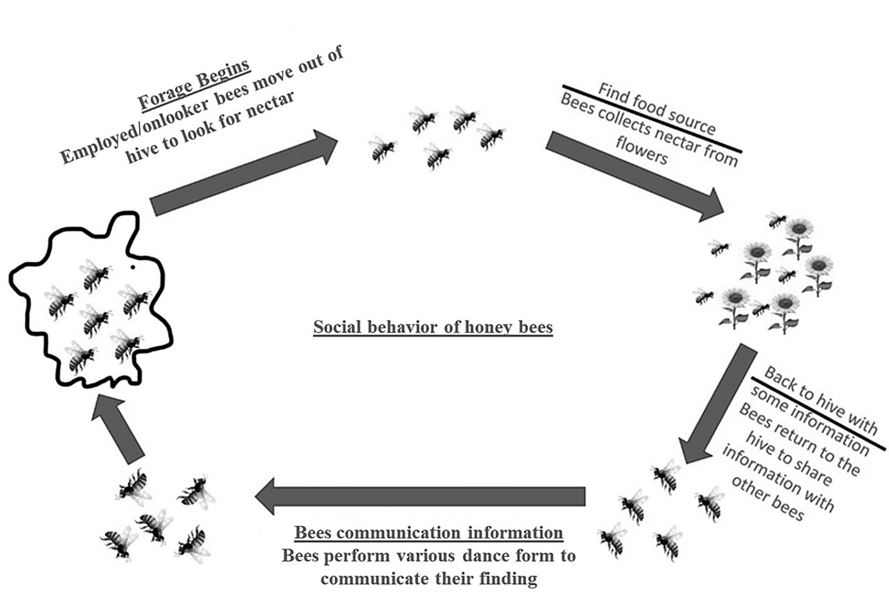

FIGURE 9.4
Social behavior of honey bees.

around for the highly dimensional space search. In the ABC method, these bees combined the local search methodology for searching neighborhood sources of food; this process is known as the exploitation process, performed by the onlooker and employed bees, with the new region search through global food sources; this process is called exploration process (Babaeizadeh and Ahmad 2014), which is performed and managed by scout bees in an attempt to search for the best source of food for the colony.

During the food search, the larger number of honey bees are considered to be onlooker bees. To socially communicate with each other, waggle dance movement was performed (Figure 9.4). With this movement, scout bees update the employed honey bees about the superiority of the food source (Wang et al. 2010).

9.7 Novel Modified ABC (MABC)

A new modified artificial bee colony (MABC) is generally created using adaptive steps with exponential functions. This MABC is mainly used as an opposition-based theory for learning and an *S*-type improved method was used for grouping, and the MABC initial population is given for the original

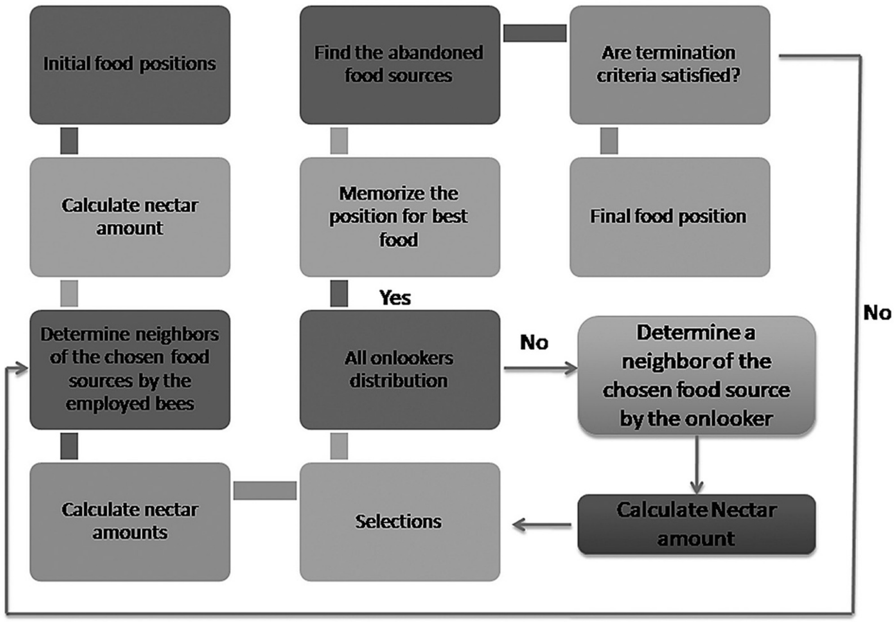

FIGURE 9.5
Different steps followed by a honey bee in ABC.

way of the roulette wheel sensitivity-pheromone selection (Figure 9.5 and Table 9.1). Particularly, an exponential adaptive step will design the functions for the replacement of the original step randomly, and the number of bees (onlooker and employed) are equal (Mohapatra et al. 2017; Kashan et al. 2012). This follows the many advantages of the ABC methodology such as simplicity, implementation ease, and performance that are also outstanding. There are, however, many flaws in the ABC algorithm: (i) The initial population generates the leading solution for a randomly dispersed population in the space. Therefore, the ability of searching is directly affected by it. (ii) All the bees begin to direct search in whole space solution, which may lead to a reduction of searching efficiency. (iii) Step length is randomly used for population regeneration. The search range should be usually restricted when the ABC performs in the neighborhood. Therefore, the optimization precision and the rate of convergence in the algorithm will be influenced (Kashan et al. 2012). Therefore, to overcome the problems with existing deficient algorithms and related ABCs, the MABC's purpose is to improve the

TABLE 9.1

Summary of ABC Algorithms' Recent Modifications

Algorithm Name	Description of Modifications	Problem	References
MABC	Incorporated Deb's rule in the selection of food sources employed and onlooker bees	Constrained Optimization	Karaboga et al. (2014)
ABC-AP	Adaptive penalty constraint and Deb's rule were used in the modification	Weight of truss structures	Sonmez (2011)
MABC	Control parameter introductions	Real-parameter optimization	Akay and Karaboga (2012)
IABC	Onlooker bee's movement was changed using universal gravitation force	Numerical optimization	Tsai et al. (2009)
ABCgBest and ABCgBestDist	Incorporated guest and distance-based reference selection movement of the onlooker	benchmark functions	Akdağli et al. (2011)
PABC-RC	Information about the integration exchange of ripple communication strategy	Benchmark functions	Liu et al. (2018)
ABC	For path search, Deb's rules were directly incorporated	Data clustering	Zhang et al. (2010)
ABC-PTS	Addition of new variables to the neighborhood search equation	Peak-to-average power ratio	Wang et al. (2020)
ABC	Addition of GRAH and two neighborhood structures for employed and onlooker bees	Generalized assignment	Baykaso et al. (2007)
ABC-PTS	Solution initialization transformation of ABC from continuous space vector into a discrete vector	Peak-to-average power ratio	Zhu and Kwong (2010)
DisABC	Use a differential expression to measure dissimilarity between binary vectors	Binary optimization	Karaboga and Basturk (2007)
ABC	Decision variables uses in indexes	Discrete optimum design of truss structures	Sonmez (2011)
OABC	Opposition concept number used	Black-Box Optimization Benchmarking (BBOB)	El-Abd (2011)

(*Continued*)

TABLE 9.1 (CONTINUED)

Algorithm Name	Description of Modifications	Problem	References
ES-ABC, MSABC, MH-ABC, and HH-ABC	ES-ABC local search, a master-slave technique in MS-ABC, multi-hive approach in MH-ABC, and combined MS-ABC and MH-ABC in HH-ABC were used	Numerical benchmark data	Gao et al. (2014)
binABC, normABC AMABC	Modified concept based on bin PSO and normalized DE, and angle-modulated PSO and DE	Binary optimization	Kashan et al. (2012)
DABC	Use of NM to start the population and local integrate search to ABC	Flow shop benchmark	Wang et al. (2020)

initial structure of the population, the consortium of the population, and the renewal of the ABC population. The MABC follows the following steps:

i. Initialization phase
CS/2 = Number for food, this is equivalent to half the colony size in the number of food sources for population initialization based on opposition learning
Fitness values calculations
Grouping of S-type sub-population
Zero = trials (Food Number 1). Trial should be zero
Initialized elitists of food sources
For memorization of the finest source of food, Iter = 0; while by sensitivity-pheromone Iter ≤ max iteration selects better elitist
Food number for employed bees' $i = 1$
Generate a new solution and update each food source step length
New solution evaluation

Iter = Iter + 1

The selection of sensitivity-pheromone was applied in between the present solution i and its other solution. Other solutions were applied if it is better than the present solution, i.e., the probability conditions.

ii. Onlooker bees
Food source selection by sensitivity-pheromone
For every onlooker bee, each source of food generates a new solution and updates the length of steps

Iter = Iter + 1

Selection applied to the sensitivity-pheromone to current solutions. But the existing resolution is better than the others. Otherwise, increasing its experimental counter-optimal solution should be memorized.

iii. Scout bee's phase
The food source determination of the trial counter should exceed the "limit" value, or in each interaction, only one scout bee was acceptable.
The scout bee used for random Food Number search ≥ max iteration returns to the optimal solution at the end.

9.8 Effect of Different Parameters in ABC of Enzyme Optimization

ABC algorithm should be more productive in terms of the scout bee's food source number (N), food source amount (M), elected food source number, dispatched bee's number to the elected food source (Nre), the bee's dispatched number to another source of food (Nsp), search area radius (Ngh), and iteration number (I_{max}) (Zhang et al. 2010). Initial food source locations with the conditions are represented within the well-defined problem for this algorithm.

$$X_{ij} = X_j^{\min} + \mathrm{ran}(0,1)\left(X_j^{\min} - X_j^{\min}\right) \tag{9.3}$$

where $i = 1, \ldots, N$ and $j = 1, \ldots, j$ are ranges in the equation. N is the number of parameters. In every area, subsequently, the new solutions created during ABC algorithm V_{jk} within X_k are demonstrated in Equation (9.4):

$$V_{jk}(t+1) = X_{jk}(t) + \varphi_{jk}(t)\left(X_{jk}(t) - X_{wk}(t)\right) \tag{9.4}$$

$$K = \mathrm{int}(rand\, X\, N) + 1$$

where $ø_{jk}$ and X_{jk} represent the random numbers uniform distribution and the jth solution from among the solution set of the kth parameter. Though, the $ø_{jk}$ area and parameter k are selected casually from the domains [1 and −1] and [1 and N], respectively.Beyond these situations, the explanation for each problem in a suitable way is replaced by the earlier one. The earlier solution is replaced if the new solution is more adaptable. After that, solutions for each bee are selected by the scout bees (Liu et al. 2018).

9.9 Control Parameters in ABC for Optimization

ABC optimization/adjustment of parameters are designed, after which the analysis was performed using the most appropriate design for the optimization of parameters. ABC algorithm can deliver the best parameters after the optimization of the process. The earlier ABC version was most efficient for basic functions. Although the performance of the ABC algorithm convergence was not that much effective when working with composite and non-separable constrained related problems and functions (Karaboga et al. 2014; Sonmez 2011). The convergence rate and improvement (Karaboga and Basturk 2007) were analyzed by the effect rate of perturbation which controls frequency change parameters; this method is commonly known as the scaling factor which determines the magnitude of parameters by changing neighboring solutions and the parameter limit by ABC performance; the modified version is proposed for solving efficient optimized problems for real parameter. Common modifications in the Artificial Bee Colony Algorithm (ABCA) are made in the perturbation process for controlling the frequency of perturbation. Frequency is fixed in the basic version of ABC while producing the new solution, with slow rate of convergence in only one parameter; this is the parent solution for the expected outcomes. But in the proposed ABCA (Mohapatra et al. 2017), a new control parameter – the modification rate (MR) – was introduced.

9.10 ABC Algorithm Modifications

Presents changes in the ABC subsection may cause the variations which are observed by different researchers in the relationships with modified tuning in the parameter, for enhancement or performance improvements. For tackling the constrained problems related to optimization, in the ABC selection procedure, the worker bees generally used Deb's rules to regulate the strategy in the procedure, instead of the greedy procedure for selection. The ABC's new variant performance was linked with two methods, i.e., PSO and DE, wherein the results are comparable and the ABC performance was clearly observed. For large-scale problems' solutions, the ABC is applied (Karaboga and Basturk 2007). The limited handling techniques were applied to the selection phase of ABC so that the feasible area of the whole search space could be reached. To choose the onlooker and employed bees, Deb's rules were incorporated. Three strategies were carried out for the selection and modification of the ABC. The modification in the three strategies selection in ABC was reported by Zhu and Kwong (2010) for numerical benchmark optimization. Modification in food source selection was carried out by onlooker bees for the prevention of premature convergence and population diversity increases. These strategies include selection based on rank selection-based selection (RABC), tournament selection (TABC), and disruptive selection of (DABC). Modified ABC performance is mainly associated with the results of basic and modified ABC as demonstrated by three selection strategies, and are used for population diversity improvement and convergence prevention.

9.11 Summary of ABC

1. Foraging behavior generally inspired by honey bees in ABC
2. For optimization purposes, ABC is used globally
3. Numerical optimization initially is proposed (Karaboga and Basturk 2007)
4. Combinatorial problems are analyzed for the optimization process (Pan et al. 2011)
5. It is also used for unconstrained and constrained problems related to optimization (Djaballah and Nouibat 2022; Karaboga et al. 2014; Kasihmuddin et al. 2021)
6. The user predetermines the employed control parameters (i.e., population size, number of maximum cycles, and limit)
7. It is comparatively simple, flexible, and robust (Rao et al. 2008; Singh 2009; Lin et al. 2021)

9.12 Application of ABC

The ABC has become the most common because of its ease of application and robustness. Researchers successfully applied the solution to complications in many different areas. First, the ABC applied to the mathematical problems by Karaboga et al. (2014) was extended to constrained optimization problems, and were then applied to neural networks of the brain (Karaboga and Basturk 2007), classification to the medical patterns, and clustering problems (Table 9.2) (Seyman and Taşpınar, 2013; Ilie and Bădică 2013).

TABLE 9.2

Applications of ABC in Different Fields

S. No.	Application of ABC	Reference
1	ABC is used for training the multilayer perceptron neural network for classifying the acoustic emission signal toward their particular source	Omkar and Senthilnath (2009)
2	Investigation of the comparison of the RBF neural network training algorithms in inertial sensor-based terrain classification	Kurban and Beşdok (2009)
3	In underbalanced drilling, they used ABC for the training of neural networks for bottom hole prediction of pressure	Irani and Nasimi (2011)
4	For modeling daily reference evapotranspiration (ET), they applied ABC in neural network training	Ozkan et al. (2011)
5	Used ABC to design the cloning template of goal-oriented C for cellular networks of neural architecture	Parmaksızoğlu Selami and Alçı Mustafa (2011)
6	Proposed an ABC-based methodology for the synthesis of neural networks	Garro et al. (2011)
7	They introduced the integrated system in which the wavelet transforms and neural network recruiting is majorly based on ABC stock forecasting	Hsieh and Yeh (2011)
8	They described a methodology based on ABC for maximizing the accuracy and minimizing the connection numbers for artificial neural networks through synaptic weights involvement	Kurban and Beşdok (2009)
9	ABC was used for MLP training and presented that the performance of MLP-ABC is improved than MLP-BP used for data of time series	Shah et al. (2012)
10	S-system neural networks were described as the basics of ABC neural network models for biochemical networks	Yeh and Hsieh (2012)

9.13 Conclusions and Future Prospects

The real-world complexity of the problems related to optimization increases the attractiveness of robust, fast, and accurate optimizers among scientists from different areas. Over the continuous and discrete spaces, ABC algorithm optimization is a newer and simpler population-based approach to optimization. It is a flexible and straightforward ABC algorithm that requires fewer parameters than the other algorithms. The original ABC algorithms and their modifications and hybrid algorithms are used for solving the optimization problems that are continuous, constrained, combinatorial, multiobjective, binary, chaotic, etc. Solving the various problems related to performed experiments from the literature proves that the ABC's efficiency, accuracy, and effectiveness are applied to all problems related to ABC. Reportedly, it has outperformed some EAs and other heuristic search tests for the benchmark problem of the real world. However, few control parameters are used and efficiently used to solve the problems related to multimodal and multidimensional optimization (Zhang et al. 2021). For the initial parameter's values, the ABC is not sensitive and is affected by increasing problems related to dimension, which is not similar to the other probabilistic algorithms related to optimization. ABC also has the inherent drawback of premature convergence and stagnation which adds to the capability loss of ABC in exploration and exploitation (Sharma et al. 2021). Although in the last two years, there have been many publications, there still exist many open complications and new areas of application where it should be useful, and also exist various dimensions in which this algorithm should be improved. Approximately, forthcoming critical research directions in the area of ABC are as follows. Complete search space investigation and management of region for optimal solution should be balanced by maintaining the diversity in the initial and future iterations for any arbitrary search algorithm for numbers. The updated equation for employed and onlooker bees phase in ABC should be as follows:

$$v_{ij} = A \times x_{ij} + B \times \left(x_{ij} - x_{kj} \right) \tag{9.5}$$

That is, modified position v_{ij} is the weighted sum of the food source position x_{ij} and the difference $(x_{ij} - x_{kj})$ of two positions of the source of food, where A is the mass of the target source of food and B is the mass difference of casual source of food. In a basic ABC, A is usually set to 1, while B is distributed uniformly in real numbers randomly (ϕ_{ij}) in the range [–1, 1]. Numerous studies were carried out on variations in ϕ_{ij} for a better mechanism of investigation (Karaboga et al. 2014). Moreover, for better outputs, the value and the range should also be fine-tuned. For the improvement in performance, effective modifications and implementation in the ABC should be done. It can be observed that many parts of the ABCA can be run in parallel. To estimate the performance and fitness, there is only one way, that is, parallel implementation should be there for every solution. Otherwise, the bees are distributed in the various processors which does not allows them improvement in the independent solution. Though this approach should be affected by the bee's dependencies in between, implementation parallel to the ABC should be considered for the shared memory of architecture, which overcomes these dependencies. The basic phase of onlooker bees in the ABC (Zhu and Kwong 2010) uses a roulette wheel selection scheme in which the fitness value of each slice is directly proportional to the size in selecting a suitable source of food. ABC is the multiobjective optimization for the solutions of the problems in which we have to optimize simultaneously two or more objectives (Banharnsakun et al. 2010). As the objective numbers increase, the Pareto-based conventional methods such as MOEAs may perform poorly. To solve this problem, the ABC multiobjective variants should be extended to research in features (Gao et al. 2014).

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