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RECENT ADVANCEMENTS IN ARTIFICIAL BEE COLONY(ABC) ALGORITHM: A SURVEY

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ABSTRACT

In modern times, Swarm Intelligence (SI) has in- spired many of the foundational works in the emerging research field of soft computing. The Artificial Bee Colony (ABC) algorithm is an SI based optimization algorithm which depends on the intelligent food seeking behaviour of honey beesswarmin nature. Various researchers have modified ABC to make it more effective and applicable to various streams of science, management, and engineering. This work shows a basic survey on ABC modifications and applications that have been carried outrecently.

Keywords: *Swarm Intelligence (SI); Artificial Bee Colony algorithm; Optimization; Foraging behavior.*

I. INTRODUCTION

Swarm Intelligence (SI) is an area which consists of many individuals that coordinate with each other using decentralized control and self-organization. Swarm Intelligence is a meta- heuristic technique for solving optimization problems [5]. It implies the mutual intelligent behavior of social creatures like bees, termites, ants, etc. Complex problems can be resolved by utilizing the ability of social learning of social creatures. Researchers have examined those behaviors and design the algorithms to solve combinatorial optimization, nonlinear or nonconvex problems in science and engineering domains. Optimization problems come across in various science and engineering fields.

Some popular SI based algorithms are Artificial Bee Colony Optimization (ABC) [14], Particle Swarm Optimization (PSO) [18], Spider Monkey Optimization (SMO) [6], Grey Wolf Optimizer (GWO) [25] etc. Both exploitation and exploration are the crucial mechanisms in a robust search process. Exploitation utilizes the existing perception to bias the search whereas exploration method is linked to the independent search for an optimal solution. The ABC algorithm was presented by Dervis Karaboga [14] in 2005. It has been used to obtain an ideal solution of numerical optimization problems. It is motivated by the intelligent food seeking behavior of honey bees. ABC algorithm is comparatively flexible, simple, fast and robust.

ABC is widely studied and used in solving many real world problems. Here it shows an overview of recent ABC advancements and applications.

II. FUNCTIONING OF HONEY BEES

ABC algorithm get inspiration from the food seeking be- havior of honey bees in nature. The swarm of honey bee follows a collaborative intelligent manner for the searching of food. The swarm has numerous qualities like exchanging the information, remembering the environment, storing the data and taking decisions after that. Updation of the swarm is being done according to the changes in the environment. Honey bees functioning could be classified as

- Food source
- Employed Bees
- Unemployed Bees
- Foraging Behavior
- Dance

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Food Source
Firstly a specific flower (or food source)isselected.The bee accumulates the data regarding the quantity of nectar present in the food source, how simply it could be taken out from the flower, in what direction and how far it is from the nest. This information stored in one unit termed as the total profitability of the source.

Employed Bees
The employed bees linked to a peculiar food source which they are presently exploiting or are employed. Each of them carries the profitability of the related food source.

Unemployed Bees
The information gathered by employed bees shared with other groups of bees known as unemployed bees. There are two groups of unemployed foragers: scout and onlooker bees. Scout bees find the brand-new food sources while the onlooker bees collect the info from the employed ones and after evaluating the data, chooses the food source.

Foraging Behavior
Foraging behavior is another feature of a honey bee swarm. In this process, honey bees step out from the hive and start exploring the food sources in the environment. After getting a food source, nectar removed from it. The nectar is stored in the stomach. Emission of enzymes in the stomach results in generating honey. Bee empties the nectar into empty cells when they return to the hive. After then, various types of dance are performed in order to share this information with other bees in the hive.

Dance
Various type of dances are performed by the employed bee to tell other bees about their food source characteristics like its plentifulness, direction and distance. Some of the dances performed by them are round dance, waggle dance, tremble dance. The dance moves are done on various parts of the hive.

By providing this information the bee wants to share whether the other bees should pursue her food source or not.

III. ARTIFICIAL BEE COLONY (ABC) ALGORITHM

The main motive after the development of numerous swarm based optimization algorithms is collective intelligence of homogeneous agents. Swarm based optimization algorithms discover solution via mutual error and experimentation technique. The location of a food source in ABC algorithm depictsan optimal solution of the problem, and the quality of solutionis termed as fitness. Three categories of bees in the colony are employed bees, onlooker bees and scout bee. The count of employed ones is identical to the onlooker ones. The employed bees are equivalent to the number of food sources. The employed bee becomes a scout bee when its food source is exhausted.

The key points of ABC algorithm are as follows [16]:
Initialize REPEAT
Employ the employed bees to the food sources and compute their nectar proportions.
By the information given by the employed bees, the onlooker bees step onto the food sources and provide the nectar amounts.
For the purpose of exploration, migrate the scout bees to find new food sources.
Remember the finest food solution observed until now.
UNTIL (preliminary are fulfilled)

The algorithm has a cycle of four stages named as Initialization stage, Employed bees stage, Onlooker bees stage and Scout bees stage. All of them are explained below:-

Initialization Stage

The initial populace of possible solutions is formed by SN positions of food sources. A food source y_i(i= 1, 2, ..., SN), is a randomly generated D dimensional vector obtained by equation 1 that represents the number of optimization parameters.

$y_{ij}=y_{minj}+random(0,1)(y_{max,}\, y_{minj}), j = 1, 2, ..., D$(1)

where$y_{minj}$and $y_{maxj}$are maximum and minimum bounds of $y_i$in j^{th}direction.

Employed Bees Stage

Now the employed bees improve their present solution in this phase. The fitness value of the new solution and the knowledge of individual understanding helps in updating their position.If the fitness or robustness of the current food source is greater than the former one, the bee renews her positionwith the current one while discarding the former value. Therefore, a greedy choice is applied here.The updated position equation forj^{th}dimensionofi^{th}candidateisasfollows

$v'_{ij}=y_{ij}+\phi_{ij}(y_{ij}-y_{lj})$ (2)

where$\phi_{ij}(y_{ij}$- $y_{lj})$ is the step size. $l$should be distinct from $i$and $\phi_{ij}$is an arbitrary number having the value ranging from -1 to 1.

Onlooker Bees Stage

Onlooker bees stage comes after the completion of em- ployed bees stage. Here every employed bee provides the fitness or robustness of the updated solutions and their location to the onlooker bees. Onlooker bees scrutinize the feasible data. After that, the selection of a solution with a probability, p_i, is done which is computed as

$$Pi = \frac{Fit\ i}{\sum_{i=1}^{SN} Fit}$$

Where Fit_i is the fitness charge of the i^{th} solution. The position update process is same as in the employed bee phase. If the calculated fitness of the new position comes out to be better than the old position, the bee retains the new calculated position and obliterate the previous position.

Scout Bees Stage

Whenever the location of the food source is not updated up to an agreed or fixed no. of cycles, at that point the food source is believed to be stucked. Now the scout bees stage begins. Here the bee which is related to the stucked source becomes a scout. Also, a randomly selected food source replaces the abandoned one. *Limit* defines the agreed or fixed no. of cycles.

Suppose the abandoned source is y_i. It is substituted by an arbitrarily chosen food source produced as:

$y_{ij}= y_{minj}+random[0, 1](y_{maxj}-y_{minj})$, for $j \in\{1, 2, ..., D\}$ (4)

where y_{minj} and y_{maxj} are the minimal and maximal bounds of y_i in j^{th} direction.

IV. RECENT ADVANCEMENTS IN ABC

Currently, a ton of experiments has been done to make ABC effective and generally applicable. Researchers have enhanced ABC with a specific end goal to dispose the disadvantages of fundamental ABC like stagnation and premature convergence from numerous points of view. The possibility of improvement in ABC can be classified in following categories:

- Presenting new policies in ABC
- Introducing changes in various phases
- Miscellaneous methods

A brief review of the above mentioned categories is as follows :

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Presenting new policies in ABC

To equalize the exploration and exploitation abilities of ABC, an adaptive variant of ABC is presented by Bansal et al. [4] in 2014. Here the value of step size and the variable limit is chosen according to the current fitness. Here good solutions (high fit) are used to exploit the search area in their neighborhood, and worse ones are chosen to explore the area. A power law-based local search in ABC (PLABC) is given by H. Sharma et al. [28] Here the exploitation capability is enhanced by generating new solutions around the best solution. The count of scout bees is increased to upgrade the exploration capability. The algorithm given by S. Jadon et al. [11] is termed as Expedited ABC (EABC). In EABC, the changes are done in the onlooker bee phase of ABC. Here the emphasis is given to a random bee having better fitness instead of a global best bee. In ABC, large step size results in skipping the true solution. A Levy flight inspired local search policy is given by H. Sharma et al. [29] to create balance among divergence and convergence in the ABC. It is then integrated with ABC. This is known as Levy Flight ABC (LFABC). In this algorithm, recent solutions are produced near the best solution thus enhancing the exploitation capability of ABC. Z. Hengwei et al. [9] in 2016 combines fuzzy C-means clustering algorithm with Artificial Bee Colony(ABC) algorithm to enhance the performance of clustering. The exploring and exploiting abil- ities get improved by presenting a neighborhood radius and global optimum into the search formula. The improved ABC clustering algorithm based on FCM improves the accuracy, the robustness to a high level andsensitivity to noise gets lowered. Further H. Sharma et al. [30] developed an improved variant of ABC namely Lbest Gbest ABC (LGABC) in which the position update process of the employed bee phase and onlooker bee phase is altered. Here, the solution updates the positions by considering the motivation from local best and global best solutions respectively.

In 2017, S. Jadon et al. [12] provided a solution to elaborate an efficient meta-heuristic algorithm that provides a better stability between exploration and exploitation capabilities and better convergence speed by hybridization of ABC and DE. In that strategy, the onlooker bee phase of ABC takes inspiration from DE. The concept of the best individual is utilized in employed bee phase and scout bee phase is also modified for higher exploration. W. Bai et al. [3] designed Improved ABC (IABC). The IABC based on the orthogonal learning was proposed to adjust the exploitation and exploration of ABC. Orthogonal learning is a strategy to predict the best combination of two solution vectors based on limited trials instead of exhaustive trials and to conduct deep search in the solution space.

Changes instages

In 2016, Syahid Anuar et al. [2] proposed a strategy called ABC rate of change (ABC-ROC) by replacing the parameter limit as the scout bee procedure relies on the rate of change on the performance graph. It keeps track of the change of the slope on the performance graph. It also revamps the conver- gence ability of the ABC. Kumar et al. [19] improved onlooker bee phase by taking inspiration from memetic algorithm to stabilize the variation and merging ability of the ABC. The modification in the onlooker bee phase is done by improved GSS method. Exploration scope of GSS method and solution modernise equality is modified by the proposed algorithm to balance the escalation and viciousness of local search space. This is termed as Improved onlooker bee phase in ABC (IoABC).

YujiaoShi et al. [31] in 2016 suggested an update equality and an enhanced dimension- selection policy for employed bees. A velocity variant is defined to examine the modification of creatures on each dimension. It gives a good stability among global search and local tuning capabilities. The improvement in ABC attains more beneficial results than the other algorithms.

Miscellaneous

Karaboga, B. Gorkemli [17] in 2014 proposed a different type of ABC called quick artificial bee colony(qABC) algorithm in order to model the action of onlooker bees more perfectly. It also enhances the convergence performance of classic ABC. D. Karaboga and Selcuk Aslan [15] in 2015 proposed a newmig rant modeling scheme for parallel artificial bee colony algorithm. Here best solutions are combined to increase the status of the distributed source. The convergence capability of the parallel ABC algorithm and the quality of the final solution is increased. CelalOzturket al. [27] gave an innovative binary category of the ABC algorithm centered on genetic operators (GB-ABC) like crossover and swap to resolve binary optimization problems. It is simpleto implement. It can be applied to diverse kind of binary problems such as dynamic image clustering and knapsack problems.G. Yavuzand D. Aydin [36] proposed Angle Modulated Artificial Bee Colony (AMABC) algorithm in 2016 for optimal feature selection. A service-oriented artificial bee colony algorithm(S-ABC) has been presented by Xia of eiXuetal.[35] in 2016 to focus on optimization problems in service domain environments. Firstly the key service area features are defined and then their impact on solving service optimization problems is analyzed. The ability and usefulness of solving service optimization algorithm is improved by S-Abc. An additional ABC modification named ABC with memory algorithm (ABCM) was proposed by Xianneng Li and GuangfeiYang [20]. Memory mechanism is used to retain their past successful knowledge of for aging action. A strategy for the choice of neighbors is developed by Wan- li Xiang et al. [34] has been introduced in 2017. It stands on grey relational degrees among a present individual and its neighbors. Then, the selected neighbor is used to lead the search process. Information of the best individual in solution search equations, an opposition-deployed training system and a chaotic initialization approach are joined together and form a grey artificial bee colony algorithm(GABC).

An efficient solution approach based on an ABC algorithm with feasibility enforcement and infeasibility toleration procedures for solving cardinality constrained portfolio optimization problem was proposed by Can B. Kalayaci in 2017 [13].

In 2017 ABC algorithm is analyzed on constrained optimization by Bahriye Akay and Dervis Karaboga [1]. Also, some modifications are done and then the performance of the algorithm is scrutinized. When integration of DE operators into ABC's algorithm's employed and on looker's phase is done then best solution and stability is improved. In 2017 Li et al. [21] integrate variable neighborhood search (VNS) with ABC algorithm to accelerate the local search. This algorithm is known as variable neighborhood ABC (VNABC). It solves continuous global optimization problems (C-GOPs). It accelerates the optimization performance of ABC. FuliZhong et al. [39] presented MNIIABC algorithm. Here, a modified-neighborhood-based update operator and a subset- best guided term is implemented in the employed bee phase. An independent-inheriting-search scheme is applied in the onlooker bee phase to enhance the exploitation.

Liang et al. [22] suggested an improved ABC (I-ABC) algorithm for COPs. Relaxing the Debs rules, adopting the rank selection method for onlooker bees to pick the food sources to exploit, is done in this scheme. Two adjustive control parameters are constructed to select the best-so-far solution.

V. APPLICATIONS

Various real world issues can be resolved by using ABC. The areas or applications in which ABC has been applied successfully are as follows:-

Vehicle Routing Problem

Mingprasert et al. [24] in 2017 provided an adaptive ABC to manage the goods transportation routing issue based on available capacity of vehicles well-known as Capacitated Vehi- cle Routing Problem (CVRP). The traditional ABC algorithm has been modified to provide a good quality solution and performance. This algorithm verified through VRP Benchmark problems by comparing the results with existing Best Known Solutions (BKS) of the Capacitated VRP benchmark.

Modified ABC for cloud manufacturing

Jiajun Zhou and Xifan Yao [40] in 2017 gave a novel strategy, called multi-population parallel self-adaptive differ- ential ABC (MPsaDABC) algorithm for an NP-hard CCSOS problem. It blends the benefits of DE and ABC with multi- population coevolution scheme. For complex CCSOS problems, it has shown better performance than other population algorithms.

Fire Detection Method of Mine Belt Conveyor

Liu Yuxin, Ma Xianmin [37] in 2017 gave another very important application in ABC. A method of integrating image processing with Artificial Bee Colony algorithm, gray scale morphology, and information entropy was

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introduced. In ABC algorithm, the best threshold comes close in parallel through cooperation and information sharing of employed, onlookers and scouts bees and the division of labour. Gray scale morphology used to reduce image noise. It can effectively decrease the labor cost and the false positive rate.

Range Image Registration

Range image registration is a captivating subject in the field of image processing. Iterative Closest Point(ICP) algorithm is used for registration. To overcome the limitations of ICP algorithm, an enhanced ABC algorithm for range image reg- istration was introduced by Xiao Lu et al. [23] in 2016 termed as PABC algorithm. Another solution modernizing scheme presented and infused into the ABC, taking inspiration from particle swarm optimization algorithm. It enhanced the search ability of ABCalgorithm.

Urban Traffic Light Scheduling Problem

Kaizhou Gao et al. [8] in 2017 presented a centralized traffic network prototype to narrate the city traffic light scheduling problem (UTLSP) in a traffic network. The purpose was to reduce the network-wise total delay time of all vehicles in a fixed time window. An IABC algorithm (Improved ABC) was intended for solving the potentially high computational complexity intricate in UTLSP and also to reduce the entire delay time of traffic network within a specified time.

Solving job shop scheduling issue

In 2015 S. Sundar et al. [33] presented a Hybrid ABC (HABC) algorithm with an aim of reducing the makespan amid all the jobs for detecting good value results of the JSPNW. It is a supplement of JSP subjected to the limitation that there is no waiting time permitted for the operations for a given job. The coordination of various components of ABC algorithm provides the high quality solutions for the JSPNW by initialization, selection, and local search.

Economic Lot Scheduling Issue

In the study given by Shih-Cheng Horng [10] in 2015, the SELSP generated as a fixed-sequence base-stock (FSBS) scheme including capacity confined lot-sizing strategy. Com- bination of ABC and ordinal optimization (OO) theory, termedas ABCOO was presented. The benefits of both the algorithms are in it.

Dynamic green bike repositioning problem

C.S. Shui, W.Y.Szeto [32] in 2017 introduced a new dynamic green bike repositioning problem (DGBRP) that at the same time minimizes the total unmet demand of the bike-sharing system and CO_2emission cost and the fuel of the repositioning vehicle over particular stipulated time. An enhanced artificial bee colony (EABC) algorithm and a route truncation heuristic were used to optimize the route design in each stage.

Fabricdyeing

Fabric dyeing is a fundamental manufacturing procedure in the garment industry. Due to the consumption of high energy and emission of pollutant in water, dyeing process requires careful scheduling to reduce the costs. In 2017, RuiZhang et al. [38] presented the dyeing action scheduling issue as a bi-objective parallel batch-processing machine scheduling model. An effective multi-objective ABC (MO-ABC) algorithm suggested for resolving the scheduling problem to obtain satisfactory schedules in appropriate time.

VI. CONCLUSION

This study presents a detailed survey about the recent advancements and applications of Artificial Bee Colony (ABC) algorithm. Firstly the social functioning of honey bees is narrated and then the basic ABC algorithm is described. After that, it provides a review of the recent advancements made in ABC by introducing new strategies, changes in phase, etc. Also, a brief overview of various applications of ABC is listed. This survey shows that ABC is a vital and dynamic field of research in coming years.

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