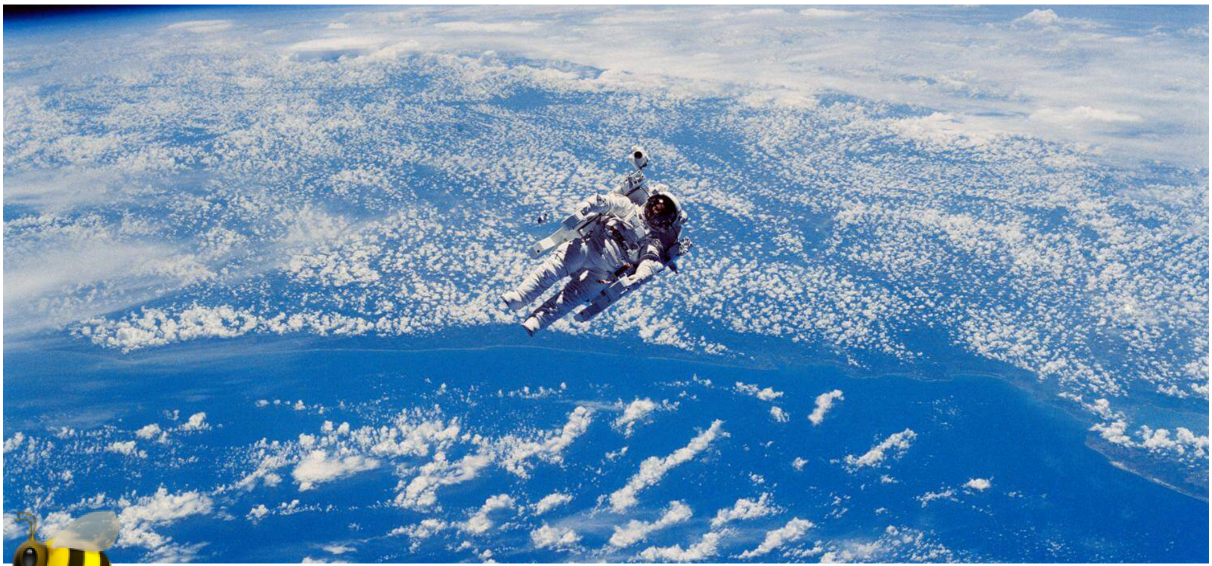

A Literature Review: Artificial Bee Colony Algorithm

Introduction

Optimization is widely used in various fields, including engineering, economics, machine learning, and many others, to solve complex problems and improve decision-making processes. Optimization refers to the process of finding the best solution or achieving the best outcome under given circumstances. This could involve maximizing something such as profit or efficiency or minimizing something for example cost or error. This can be done using various techniques, such as gradient descent, linear programming, genetic algorithms, or other optimization algorithms, depending on the nature of the problem.

Mathematical optimization methods can be computationally expensive for real-world problems due to complexity, high dimensionality, uncertainty, dynamic nature, and so on. Because of these challenges, heuristic algorithms are often preferred for real-world optimization problems. Heuristic algorithms are more flexible and can often find good solutions quickly, even in complex and uncertain environments. They are also easier to implement and can be adapted to different types of problems without requiring a detailed mathematical model. Heuristic algorithms cannot be proven to converge to the optimum solution in the solution space. Such algorithms have the property of convergence, but they cannot guarantee the exact solution. They can only guarantee a solution close to the exact solution but they can perform with lower computational cost.

Nature-Inspired Optimization (NIO) Algorithms are a subset of heuristic algorithms that are inspired by natural processes or phenomena. In general, we can classify (NIO) Algorithms into two main groups biology-inspired and physics-based algorithms, Biology inspired optimization (BIO) algorithms are a class of computational techniques that are inspired by biological systems and processes, (BIO) algorithms can be considered to consist of two subgroups which are evolutionary algorithms (EAs) draw inspiration from the mechanism of natural evolution and swarm intelligence (SI) based algorithms simulate the smart and collaborative behaviors seen in nature(Karaboğa, 2020).

The Artificial Bee Colony (ABC) algorithm is one of the swarm intelligence-based optimization algorithms and it is inspired by the foraging behavior of honey bees. It was proposed by Derviş Karaboğa for optimizing numerical problems in 2005 (Karaboga,2005). Since then, the Artificial Bee Colony (ABC) algorithm has seen several improvements and variations. Researchers have introduced modifications and enhancements to address its limitations and improve its performance in different problem domains. the Artificial Bee Colony (ABC) algorithm has found wide applications across various fields due to its simplicity, effectiveness, and ability to handle complex optimization problems

Bee Colony

Self-organization and division of labour are two main features of swarm intelligent behaviour which allows self-organize and adapt to the given environment. Self-organization refers to the process where a system's individual parts interact in a way that, without any central coordination, leads to the emergence of ordered structures at the system's global level. This occurs through basic rules governing interactions among the system's components, which rely solely on local information and do not consider the overall pattern of the system. These rules are positive feedback, negative feedback, fluctuations, and multiple interactions. Division of labor occurs when specialized individuals perform different tasks simultaneously. This approach is more efficient than having unspecialized individuals perform tasks sequentially. Division of labor also allows the swarm to adapt to environmental changes (Bonabeau,1999).

When bees are examined in terms of food search, the bee swarm consists of three basic parts. these are food sources, employed bees, and unemployed bees. Employed bees are responsible for carrying nectar from a certain food

source and sharing information about the source they exploit. Unemployed bees are divided into two groups, scout bees and onlooker bees. Scouts explore the environment around the nest to find new food sources, onlookers wait in the hive and observe the shared information by the employed bees to choose the best food source to exploit.
The most critical aspect of forming collective knowledge in a hive is exchanging information among bees. The dancing area is the most crucial part of information exchange. Bees communicate about the quality of food sources in this area through a dance known as the waggle dance.

Since an onlooker bee observing the dance area has access to information about all the current rich food sources, she can watch numerous dances and decide to exploit herself at the most profitable source. In this way, the more profitable a resource is, the more likely it is to be visited by onlooker bees(Tereshko,2005).

The duties of the bees mentioned above are not fixed and may change depending on the situation. For example, when a food source is exhausted, employed bees abandon this source and start looking for new food sources by taking on the role of scout bee, or it can be an onlooker bee and wait in the hive. An onlooker bee can become an employed bee for carrying nectar from a food source or may become a scout bee and begin to look for a new food source according to conditions and its internal motivation.

Basic Artificial Bee Colony Algorithm

The Artificial Bee Colony (ABC) algorithm simulates the foraging behavior of real honey bees for solving multidimensional and multimodal optimization problems(Karaboğa,2010). In the artificial bee colony algorithm model, the colony is divided into three groups: employed bees, onlookers, and scouts. The first half of the colony comprises employed artificial bees, while the second half consists of onlookers. Each food source is assigned to only one employed bee. When a food source is exhausted, the employed bee associated with it becomes a scout.

Here is a structured version of the algorithm based on the steps you provided:

1. **Initialization(Scout bee Phase):** Send the scouts to search for new food sources randomly.

2. **Repeat Until Requirements are Met:**
   a.Employed Bee Phase: Send the employed bees to the food sources and

determine their nectar amounts. Calculate the probability value of each food source to be chosen by the onlooker bees based on the nectar amounts.
b. Onlooker bee Phase: Send the onlooker bees to the food sources based on the probabilities and determine their nectar amounts.
d. Scout Bee Phase::Stop the exploitation process of the sources that are exhausted by the bees. employed bees related to exhausted food sources become scout bees and find a new food source randomly.
e. Memorize the best food source found so far.

Initialization Phase

Xm represents the m number of solution vectors of the objective function. Each Xm solution vector consists of n number of variables which is indicated by i.

The following equation may be used for initialization purposes (1):

$$Xmi = li + rand(0,1) * (Ui - Li)(1)$$

Where *Li* and *Ui* are the lower and upper bound of the parameter X*mi*, respectively.

Employed Bees Phase

Employed bees search for new food sources (*Vm*) having more nectar within the neighborhood of the food source (*Xm*) in their memory. They find a neighbor food source and then evaluate its profitability (fitness). For example, they can determine a neighbor food source (*Vm)* using the formula given by equation (2):

$$Vmi = Xmi + \phi mi(Xmi - Xki)(2)$$

where *Xk* is a randomly selected food source, *i* is a randomly chosen parameter index and *ϕmi* is a random number within the range [−*a*,*a*]. After producing the new food source *Vm*, its fitness is calculated and a greedy selection is applied between *Vm* and *Xm*.

The fitness value of the solution, *FİTm(Xm)*, might be calculated for minimization problems using the following formula (3)

$$FITm = \begin{cases} \frac{1}{1+Fm(Xm)} & \text{if } Fm(Xm) \geq 0 \\ 1 + |Fm(Xm)| & \text{if } Fm(Xm) < 0 \end{cases} (3)$$

where *Fm(Xm)* is the objective function value of solution *Xm*.

Onlooker Bees Phase

In the Artificial Bee Colony (ABC) algorithm, the unemployed bees are divided into two groups: onlooker bees and scouts. Employed bees share information about their food sources with onlooker bees, which are waiting in the hive. In the ABC algorithm, an onlooker bee selects a food source based on probability values calculated using the fitness values provided by the employed bees. To perform this selection, a fitness-based technique such as the roulette wheel selection method can be used. This method assigns probabilities to food sources based on their fitness values, allowing the onlooker bees to make informed decisions about which sources to exploit.

The probability value *Pm* with which *Xm* is chosen by an onlooker bee can be calculated by using the expression given in equation (4) :

$$p_m = \frac{FITm(Xm)}{\sum_{m=1}^{SN} FITm(Xm)} (4)$$

After a food source *Xm* for an onlooker bee is probabilistically chosen, a neighborhood source *Vm* is determined by using equation (2), and its fitness value is computed. As in the employed bees phase, a greedy selection is applied between *Vm* and *Xm*. Hence, more onlookers are recruited from richer sources and positive feedback behavior appears.

Scout Bees Phase

In the Artificial Bee Colony (ABC) algorithm, the unemployed bees that randomly choose food sources are called scouts. Employed bees whose solutions cannot be improved after a certain number of trials, specified by the user as the "limit" or "abandonment criteria," become scouts, and their solutions are abandoned. The converted scouts then start to search for new solutions randomly. If a solution (*Xm)* has been abandoned, the new solution discovered by the scout who was the employed bee of (*Xm)* can be defined by Equation (1) in the provided source. This process helps in abandoning initially poor or exploited sources, leading to a balance between positive and negative feedback behavior in the algorithm.

Improvements on Artificial Bee Colony Algorithm

The integration of machine learning (ML) algorithms into nature-inspired optimization (NIO) algorithms, such as the artificial bee colony (ABC) algorithm, has become popular due to NIO's effectiveness in solving complex optimization problems. By leveraging ML's ability to generate knowledge from data, researchers have enhanced the performance of ABC and other NIO algorithms. These hybrid approaches aim to create more intelligent versions of ABC, improving its effectiveness in solving optimization problems in various fields, including ML. This integration has led to numerous studies combining ABC with ML techniques, contributing to the advancement of both fields.

Integrating machine learning (ML) techniques into the artificial bee colony (ABC) algorithm can significantly enhance its performance across various stages. During initialization, ML can help generate initial solutions more effectively by sampling the search space based on data from previous solutions, leading to a better initial population. In producing trial solutions, ML algorithms can guide employed and onlooker bees to select the most suitable neighbor solutions, improving search efficiency. ML can also assist in maintaining diversity in the population by determining solutions for onlooker bees, particularly beneficial for multi-modal or multi-objective problems. Additionally, ML can aid scout bees in discovering better solutions in unvisited regions of the search space, enhancing exploration. By using ML models to represent the real objective function, the fitness values of solutions can be predicted more quickly, especially useful in cases where direct evaluation is time-consuming. Furthermore, ML techniques can help scale down large-scale problems and simplify the optimization task for ABC. Adaptive control parameters and strategies can be achieved by employing ML, which can adapt parameters based on the evolutionary states of the algorithm and determine the best strategies for operations based on collected data, ultimately improving the overall performance of the ABC algorithm. In his study in 2020, Karaboğa examined the studies in which machine learning algorithms were applied to different stages of the ABC algorithm. (karaboğa,2020)

Applications of The ABC Algorithm

The Artificial Bee Colony (ABC) algorithm, inspired by the foraging behavior of honey bees, has found applications in a diverse array of optimization problems. Some notable examples are optimizing neural networks (Karaboğa, 2007; Karaboğa, 2008), configuring distribution networks to reduce losses (Rao, 2008), camera calibration using the direct linear transformation method

(Bendes, 2008), designing digital IIR filters (Karaboğa, 2009), economic load dispatch with valve-point effect using the artificial bee colony algorithm (Hemamalini, 2008).

The ABC algorithm is also very useful for medical image analysis in terms of classification, enhancement, clustering, and segmentation. In his study, Öztürk examined the studies using the ABC algorithms in the field of medical image processing. (Öztürk,2020)

These applications demonstrate the versatility and effectiveness of the ABC algorithm across different domains and problem types.

References

Dervis Karaboga, Bahriye Akay & Nurhan Karaboga | (2020) A survey on the studies employing machine learning (ML) for enhancing artificial bee colony (ABC) optimization algorithm, Cogent Engineering, 7:1, 1855741, DOI: 10.1080/23311916.2020.1855741

E. Bonabeau, M. Dorigo, G. Theraulaz, “Swarm Intelligence: From Natural to Artificial Systems”, New York, NY: Oxford University Press, 1999.

Dervis Karaboga (2010), Scholarpedia, 5(3):6915 Artificial bee colony algorithm doi:10.4249/scholarpedia.6915.

Karaboga, D, (2005). An idea based on honey bee swarm for numerical optimization. Technical Report TR06, Erciyes University, Engineering Faculty, Computer Engineering Department, 2005

Karaboga D, Akay B, Ozturk C (2007) Artificial Bee Colony (ABC) Optimization Algorithm for Training
Feed-ForwardNeuralNetworks.In: Modeling decisions for artificial intelligence. LNCS, vol 4617/2007.
Springer-Verlag, pp 318–329

Karaboga D, Ozturk C, Akay B (2008) Training neural networks with abc optimization algorithm on medical pattern classification. In: International conference on multivariate statistical modeling and high dimensional data mining, Kayseri, Turkey

Rao RS, Narasimham S, Ramalingaraju M (2008) Optimization of distribution network configuration for loss reduction using artificial bee colony algorithm. Int J Electr Power Energy Syst Eng 1(2):116–122

Bendes E, Ozkan C (2008) Direk lineer trasformasyon yönteminde yapay zeka tekniklerinin uygulanmas. In:UZALCBS08, Kayseri, Turkiye

Karaboga N (2009) A new design method based on artificial bee colony algorithm for digital IIR filters. J Franklin Inst 346(4):328–348

Hemamalini S, Simon SP (2008) Economic load dispatch with valve-point effect using artificial bee colony algorithm. In: XXXII national systems conference, India

S. Öztürk, R. Ahmad and N. Akhtar, Variants of Artificial Bee Colony algorithm and its applications in medical image processing, Applied Soft Computing Journal (2020), doi: https://doi.org/10.1016/j.asoc.2020.106799

V. Tereshko, A. Loengarov, “Collective Decision-Making in Honey Bee Foraging Dynamics”, Computing and Information Systems Journal, ISSN 1352-9404, vol. 9, No 3, October 2005.