# AN IDEA BASED ON HONEY BEE SWARM FOR NUMERICAL OPTIMIZATION

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## I. INTRODUCTION

Swarm intelligence has become a research interest to many research scientists of related fields in recent years. Bonabeau has defined the swarm intelligence as "any attempt to design algorithms or distributed problem-solving devices inspired by the collective behaviour of social insect colonies and other animal societies" [1]. Bonabeau et al. focused their viewpoint on social insects alone such as termites, bees, wasps as well as other different ant species. However, the term swarm is used in a general manner to refer to any restrained collection of interacting agents or individuals. The classical example of a swarm is bees swarming around their hive; nevertheless the metaphor can easily be extended to other systems with a similar architecture. An ant colony can be thought of as a swarm whose individual agents are ants. Similarly a flock of birds is a swarm of birds. An immune system [2] is a swarm of cells and molecules as well as a crowd is a swarm of people [3]. Particle Swarm Optimization (PSO) Algorithm models the social behaviour of bird flocking or fish schooling [4].

  

Two fundamental concepts, self-organization and division of labour, are necessary and sufficient properties to obtain swarm intelligent behaviour such as distributed problem-solving systems that self-organize and adapt to the given environment:

**a)** Self-organization can be defined as a set of dynamical mechanisms, which result in structures at the global level of a system by means of interactions among its low-level components. These mechanisms establish basic rules for the interactions between the components of the system. The rules ensure that the interactions are executed on the basis of purely local information without any relation to the global pattern. Bonabeau et al. have characterized four basic properties on which self organization relies: Positive feedback, negative feedback, fluctuations and multiple interactions [1]:

**i)** Positive feedback is a simple behavioural "rules of thumb" that promotes the creation of convenient structures. Recruitment and reinforcement such as trail laying and following in some ant species or dances in bees can be shown as the examples of positive feedback.

**ii)** Negative feedback counterbalances positive feedback and helps to stabilize the collective pattern. In order to avoid the saturation which might occur in terms of available foragers, food source exhaustion, crowding or competition at the food sources, a negative feedback mechanism is needed.

**iii)** Fluctuations such as random walks, errors, random task switching among swarm individuals are vital for creativity and innovation. Randomness is often crucial for emergent structures since it enables the discovery of new solutions.

**iv)** In general, self organization requires a minimal density of mutually tolerant individuals, enabling them to make use of the results from their own activities as well as others.

**b)** Inside a swarm, there are different tasks, which are performed simultaneously by specialized individuals. This kind of phenomenon is called division of labour. Simultaneous task performance by cooperating specialized individuals is believed to be more efficient than the sequential task performance by unspecialized individuals [2,5-7]. Division of labour also enables the swarm to respond to changed conditions in the search space. Two fundamental concepts for the collective performance of a swarm presented above, self-organization and division of labour are necessary and sufficient properties to obtain swarm intelligent behaviour such as distributed problem-solving systems that self-organize and -adapt to the given environment.

## II. BEHAVIOUR OF HONEY BEE SWARM

The minimal model of forage selection that leads to the emergence of collective intelligence of honey bee swarms consists of three essential components: food sources, employed foragers and unemployed foragers and the model defines two leading modes of the behaviour: the recruitment to a nectar source and the abandonment of a source.

**i) Food Sources:** The value of a food source depends on many factors such as its proximity to the nest, its richness or concentration of its energy, and the ease of extracting this energy. For the sake of simplicity, the "profitability" of a food source can be represented with a single quantity [8].

**ii) Employed foragers:** They are associated with a particular food source which they are currently exploiting or are "employed" at. They carry with them information about this particular source, its distance and direction from the nest, the profitability of the source and share this information with a certain probability.

**iii) Unemployed foragers:** They are continually at look out for a food source to exploit. There are two types of unemployed foragers: scouts, searching the environment surrounding the nest for new food sources and onlookers waiting in the nest and establishing a food source through the information shared by employed foragers. The mean number of scouts averaged over conditions is about 5-10% [8].

The exchange of information among bees is the most important occurrence in the formation of the collective knowledge. While examining the entire hive it is possible to distinguish between some parts that commonly exist in all hives. The most important part of the hive with respect to exchanging information is the dancing area. Communication among bees related to the quality of food sources takes place in the dancing area. This dance is called a waggle dance.

Since information about all the current rich sources is available to an onlooker on the dance floor, probably she can watch numerous dances and decides to employ herself at the most profitable source. There is a greater probability of onlookers choosing more profitable sources since more information is circulated about the more profitable sources. Employed foragers share their information with a probability proportional to the profitability of the food source, and the sharing of this information through waggle dancing is longer in duration. Hence, the recruitment is proportional to the profitability of the food source [9].

In order to understand the basic behaviour characteristics of foragers better, let us examine Figure 1. Assume that there are two discovered food sources: A and B. At the very beginning, a potential forager will start as unemployed forager. That bee will have no knowledge about the food sources around the nest. There are two possible options for such a bee:

**i)** It can be a scout and starts searching around the nest spontaneously for a food due to some internal motivation or possible external clue (S on Figure 1).

**ii)** It can be a recruit after watching the waggle dances and starts searching for a food source (R on Figure 1).

After locating the food source, the bee utilizes its own capability to memorize the location and then immediately starts exploiting it. Hence, the bee will become an “employed forager”. The foraging bee takes a load of nectar from the source and returns to the hive and unloads the nectar to a food store. After unloading the food, the bee has the following three options:

**i)** It becomes an uncommitted follower after abandoning the food source (UF).

**ii)** It dances and then recruits nest mates before returning to the same food source (EF1)

**iii)** It continues to forage at the food source without recruiting other bees (EF2).

It is important to note that not all bees start foraging simultaneously. The experiments confirmed that new bees begin foraging at a rate proportional to the difference between the eventual total number of bees and the number of present foraging.

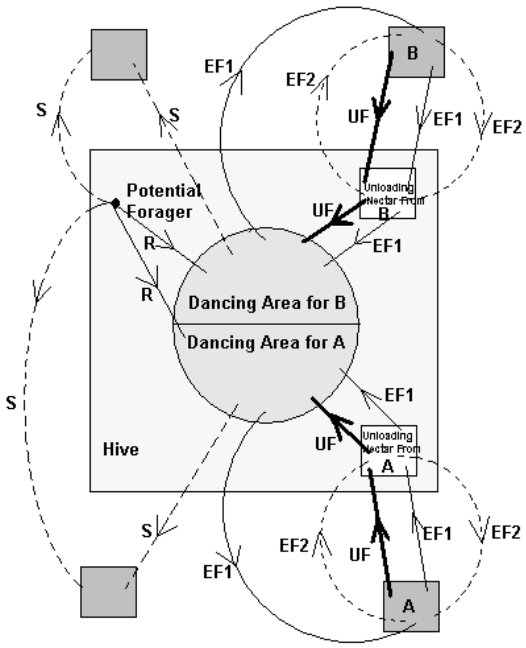


Figure 1. The behaviour of honey bee foraging for nectar

In the case of honey bees, the basic properties on which self organization relies are as follows:

i) **Positive feedback:** As the nectar amount of food sources increases, the number of onlookers visiting them increases, too.

ii) **Negative feedback:** The exploitation process of poor food sources is stopped by bees.

iii) **Fluctuations:** The scouts carry out a random search process for discovering new food sources.

iv) **Multiple interactions:** Bees share their information about food sources with their nest mates on the dance area.

## III. PROPOSED APPROACH

In this work, a particular intelligent behaviour of a honey bee swarm, foraging behaviour, is considered and a new artificial bee colony (ABC) algorithm simulating this behaviour of real honey bees is described for solving multidimensional and multimodal optimisation problems. In the model, the colony of artificial bees consists of three groups of bees: employed bees, onlookers and scouts. The first half of the colony consists of the employed artificial bees and the second half includes the onlookers. For every food source, there is only one employed bee. In other words, the number of employed bees is equal to the number of food sources around the hive. The employed bee whose food source has been exhausted by the bees becomes a scout. The main steps of the algorithm are given below:

**Send the scouts onto the initial food sources**
**REPEAT**
  **Send the employed bees onto the food sources and determine their nectar amounts**
  **Calculate the probability value of the sources with which they are preferred by the onlooker bees**
  **Send the onlooker bees onto the food sources and determine their nectar amounts**
  **Stop the exploitation process of the sources exhausted by the bees**
  **Send the scouts into the search area for discovering new food sources, randomly**
  **Memorize the best food source found so far**
**UNTIL (requirements are met)**

Each cycle of the search consists of three steps: moving the employed and onlooker bees onto the food sources and calculating their nectar amounts; and determining the scout bees and directing them onto possible food sources. A food source position represents a possible solution to the problem to be optimized. The amount of nectar of a food source corresponds to the quality of the solution represented by that food source. Onlookers are placed on the food sources by using a probability based selection process. As the nectar amount of a food source increases, the probability value with which the food source is preferred by onlookers increases, too. Every bee colony has scouts that are the colony's explorers [10]. The explorers do not have any guidance while looking for food. They are primarily concerned with finding any kind of food source. As a result of such behaviour, the scouts are characterized by low search costs and a low average in food source quality. Occasionally, the scouts can accidentally discover rich, entirely unknown food sources. In the case of artificial bees, the artificial scouts could have the fast discovery of the group of feasible solutions as a task. In this work, one of the employed bees is selected and classified as the scout bee. The selection is controlled by a control parameter called "limit". If a solution representing a food source is not improved by a predetermined number of trials, then that food source is abandoned by its employed bee and the employed bee is converted to a scout. The number of trials for releasing a food source is equal to the value of "limit" which is an important control parameter of ABC. In a robust search process exploration and exploitation processes must be carried out together. In the ABC algorithm, while onlookers and employed bees carry out the exploitation process in the search space, the scouts control the exploration process.

In the case of real honey bees, the recruitment rate represents a "measure" of how quickly the bee swarm locates and exploits the newly discovered food source. Artificial recruiting process could similarly represent the "measurement" of the speed with which the feasible solutions or the optimal solutions of the difficult optimization problems can be discovered. The survival and progress of the real bee swarm depended upon the rapid discovery and efficient utilization of the best food resources. Similarly the optimal solution of difficult engineering problems is connected to the relatively fast discovery of "good solutions" especially for the problems that need to be solved in real time.

## IV. SIMULATION RESULTS

In the simulation studies, Artificial Bee Colony (ABC) Algorithm was applied for finding the global minimum of the well-known three test functions. One of the functions is Sphere function that is continuous, convex and unimodal function. $\vec{x}$ is in the interval [-100, 100]. Global minimum value for this function is 0 and the optimum solution is $\vec{x}_{opt} = (x_1, x_2, ..., x_5) = (0,0,...,0)$. The second function is a well known classic optimization problem: Rosenbrock valley. The global optimum is inside a long, narrow, parabolic shaped flat valley. Therefore, it is very difficult to converge the global optimum. Variables of the function are strongly dependent, and the gradients generally do not point towards the optimum. $\vec{x}$ is in the interval [-2.048, 2.048], the global minimum value is 0; and the optimum solution is $\vec{x}_{opt} = (x_1, x_2) = (1,1)$. The global optimum of the function is the only optimum and the function is unimodal. The third function is Rastrigin function which is based on Sphere function with the addition of cosine modulation to produce many local minima. $\vec{x}$ is in the interval [-600, 600] and the minimum value is 0. The optimum solution for this function is $\vec{x}_{opt} = (x_1, x_2, ..., x_{10}) = (0,0,...,0)$

**Table 1**: Benchmark functions tested by the ABC Algorithm

| **Functions** | **Ranges** | **Minimum Value** |
|---|---|---|
| $f_1(\vec{x}) = \sum_{i=1}^{5} x_i^2$ | $-100 \le x_i \le 100$ | $f_1(\vec{0}) = 0$ |
| $f_2(\vec{x}) = 100(x_2 - x_1^2)^2 + (x_1 - 1)^2$ | $-2.048 \le x_i \le 2.048$ | $f_2(\vec{1}) = 0$ |
| $f_3(\vec{x}) = \sum_{i=1}^{10}(x_i^2 - 10\cos(2\pi x_i) + 10)$ | $-600 \le x_i \le 600$ | $f_2(\vec{0}) = 0$ |

In the ABC algorithm, the maximum number of cycles was taken as 2000. The percentages of onlooker bees and employed bees were %50 of the colony and the number of scout bees was selected to be one. The increase in the number of scouts encourages the exploration process while the increase of onlookers on a food source encourages the exploitation process. Parameters adopted for the ABC algorithm are given in Table 2.

**Table 2**: Control parameters adopted for the ABC algorithm

| **Control parameters of ABC Algorithm** | |
|---|---|
| **swarmsize** | 20 |
| **limit** | Number of onlooker bees *Dim. |
| **number of onlookers** | 50% of the swarm |
| **number of employed bees** | 50% of the swarm |
| **number of scouts** | 1 |

Each of the experiments was repeated 30 times with different random seeds and the average function values of the best solutions were recorded. The mean and the standard deviations of the function values obtained by ABC algorithm for the same conditions are given in Table 3.

**Table 3** The results obtained by ABC algorithm.

| Functions | Mean | Std |
|---|---|---|
| $f_1(\vec{x})$ **(5D Sphere)** | 4.45E-17 | 1.13E-17 |
| $f_2(\vec{x})$ **(2D Rosenbrock)** | 0.002234 | 0.002645 |
| $f_3(\vec{x})$ **(10D Rastrigin)** | 4.68E-17 | 2.64E-17 |

## V. CONCLUSION

In this work, a new optimization algorithm based on the intelligent behaviour of honey bee swarm has been described. The new swarm algorithm is very simple and very flexible when compared to the existing swarm based algorithms. It is also very robust, at least for the test problems considered in this work. From the simulation results, it is concluded that the proposed algorithm can be used for solving unimodal and multi-modal numerical optimization problems. In this work, the algorithm was tested on a very limited set of test problems. The simulation study must be carried out on a larger set of test functions and the performance of the algorithm must be examined in detail.

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