# A Modification of Artificial Bee Colony Algorithm Applied to Loudspeaker Design Problem


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***Abstract*—The design of electromagnetic devices is generally multimodal, multidimensional and constrained. Its simulation-based feature makes traditional optimization algorithms unsuitable to use; while metaheuristic approaches are good choices for tackling such problems. Since many electromagnetic design problems require excessive computer resources even on modern computers, attempts to improve the efficiency and effectiveness of metaheuristic approaches are thus very important research topics. This paper proposes a modification of artificial bee colony (ABC) algorithm. The design philosophy of this algorithm is to promote the convergence rate of ABC. The modified ABC algorithm is applied to solve loudspeaker design problem which is analyzed using finite element method (FEM), with promising performance obtained when compared with the original ABC, genetic algorithm, particle swarm optimization and differential evolution algorithm.**



***Index Terms*—Artificial bee colony, convergence rate, electromagnetic devices, loudspeaker.**


## I. Introduction

Generally speaking, the design optimization study of electromagnetic devices is multimodal, multidimensional and constrained. These problems are black-box optimization problems and cannot be tackled by traditional optimization algorithms. In contrast, metaheuristic approaches are suitable for dealing with such problems. Some of these metaheuristic approaches are genetic algorithm (GA), particle swarm optimization (PSO), differential evolution (DE), and artificial bee colony (ABC) algorithm and so on. The optimal design of electromagnetic devices is usually based on computer simulation. It requires a lot more simulation time when compared with those needed in mechanical design studies. Thus improving the efficiency and effectiveness of metaheuristic approaches is a very important topic area of research.

Artificial bee colony (ABC) algorithm is a recently proposed metaheuristic approach, which imitates the intelligent behavior of honey bees [1]. It achieves good performance in electromagnetic device design problems [2-3]. Moreover, experimental results show that ABC achieves promising performance compared with GA, PSO and DE [4-5]. Thus, more and more researchers are interested in the application of ABC algorithm to solve practical problems.

A cycle of the ABC algorithm involves three stages: employed bee stage, onlooker bee stage and scout stage. In contrast of GA and DE, it is noted that ABC does not contain any operation exploiting the existing genetic information of solutions in the bee colony in all three stages. This one dimensional variation of the ABC algorithm would undermine the convergence rate of ABC. Thus a one-position inheritance scheme which enables the ABC algorithm to learn from the previous history is proposed. In addition, the best-so-far solution is also used in the modified algorithm to guide the search and promote convergence of the algorithm. The modified ABC algorithm is employed to solve a loudspeaker design problem to showcase the efficiency and effectiveness of the proposed algorithm.

## II. The Modified ABC Algorithm

Initially, a colony of $N_p$ solutions is randomly created, where $N_p$ denotes the colony (population) size. Without loss of generality, the optimization problem can be taken as a minimization study. Then the algorithm goes into the main cycle shown as follows.

At the employed bee stage, $N_p$ new solutions $\mathbf{v}_i$, ($i$ = 1, 2,…,$N_p$) are generated by the following equation:

$$v_{i,j} = \begin{cases} x_{i,j} + \phi\left(x_{i,j} - x_{r1,j}\right) & \text{if } j = j1 \\ x_{r2,j} & \text{if } j = j2 \\ x_{i,j} & \text{otherwise} \end{cases}, \quad (1)$$

where; $\mathbf{x}_i$, $\mathbf{x}_{r1}$ and $\mathbf{x}_{r2}$ are three randomly chosen solutions in the current colony with $r1 \neq i$ and $r2 \neq i$; $v_{i,j}$, $x_{i,j}$, $x_{r1,j}$ and $x_{r2,j}$ denote the $j^{\text{th}}$ element of $\mathbf{v}_i$, $\mathbf{x}_i$, $\mathbf{x}_{r1}$ and $\mathbf{x}_{r2}$, respectively; $\phi \in [-1, 1]$ is a random number. $\mathbf{v}_i$ competes with $\mathbf{x}_i$ and the better one (i.e. the one with smaller function value) is saved as the new $\mathbf{x}_i$ and the algorithm then goes into the onlooker bee stage.

At the onlooker bee stage, $N_p$ candidate solutions are generated; however, unlike the employed bee stage, a solution is chosen to conduct variation according to the goodness of its function value. This indicates that good solutions (those with smaller function values) have more chance to be selected; while bad solutions (those with larger function values) have less chance to be selected. After a solution (denoted by $\mathbf{x}_{ri}$) is chosen, an onlooker bee produces a variation on this solution using the following equation:

$$v_{i,j} = \begin{cases} x_{ri,j} + \phi\left(x_{ri,j} - x_{r3,j}\right) + \varphi\left(x_{best,j} - x_{r4,j}\right) & \text{if } j = j3 \\ x_{i,j} & \text{otherwise} \end{cases} \quad (2)$$

where $\mathbf{x}_{r3}$ and $\mathbf{x}_{r4}$ are two randomly chosen solutions in the current colony with $r3 \neq ri$ and $r4 \neq ri$. $\mathbf{x}_{best}$ is the best so-far-searched solutions. Then selection is implemented by comparing $\mathbf{v}_i$ and $\mathbf{x}_{ri}$. The better one will survive and stored as the new $\mathbf{x}_{ri}$. The algorithm goes into the scout bee stage.

At the scout bee stage, if a solution has been modified and cannot be improved for a long time, for example after *limit* times, then this solution is abandoned and a scout bee is sent out. In this case, this solution is replaced by a randomly created solution:

$$x_{i,j} = x_j^l + \phi\left(x_j^u - x_j^l\right), \tag{3}$$

where $\mathbf{x}^l$ and $\mathbf{x}^u$ are respectively the lower and upper bounds of the variables and $\phi \in rand[0, 1]$.

The above three stages constitutes one cycle of the modified ABC (MABC) algorithm.

As shown in (1), a new candidate solution $\mathbf{v}_i$ can inherit one element (gene) from a randomly chosen solution. This promotes gene information exchange amongst the bee colony. As shown in (2), the variation of solution $\mathbf{x}_{ri}$ is forced towards the best so-far-searched solution $\mathbf{x}_{best}$. In short, both (1) and (2) can speed up the convergence of the algorithm.

## III. Experimental Results

In order to demonstrate the efficiency of the MABC algorithm in the study of electromagnetic problems, the design of a loudspeaker model is investigated [8]. This problem consists of the minimization of the volume of iron and magnet needed in the loudspeaker as shown in Fig. 1. The finite element method (FEM) is applied to analyze the loudspeaker model to obtain its magnetic filed distribution. Its mathematical model can be expressed as:

$$\begin{aligned} &min \quad f(\mathbf{x}) = \text{iron volume} + \text{magnet volume} \\ &s.t. \quad B_{min} - |B_{gap}| \leq 0 \end{aligned} \tag{4}$$

This problem contains 16 variables ($D$ = 16).

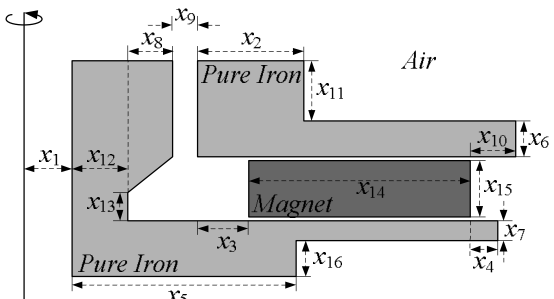


Fig. 1. A loudspeaker model.

For the MABC and ABC algorithms, $N_p$ is set to 15 and *limit* is $N_p \times D$. All algorithms are independently run 10 times with a maximum of 4500 function evaluations (maxFE=4500).

Experimental results show that the proposed algorithm is helpful for improving the performance of the ABC algorithm. Fig. 2 shows the convergence curve of MABC, ABC, GA, PSO and DE algorithms. After 1000 function evaluations, MABC converges faster and attains better solution than the other four algorithms.

Table I presents the statistics of the optimization results obtained by each algorithm over 10 runs. It is observed in this table that MABC attains better result when compared with ABC, GA, PSO and DE. The running time of MABC averaged over 10 runs is slightly slower than ABC but faster than all other algorithms. The more detailed description of the results will be given in the full paper.

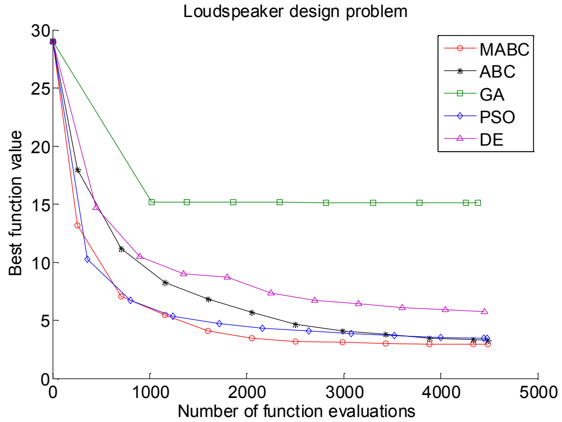


Fig. 2. Convergence curve of the best function value of MABC, ABC, GA, PSO and DE algorithms on loudspeaker design problem.

TABLE I
OPTIMIZATION RESULTS

| Algorithm | Best | Worst | Mean | Stdev | Time |
|---|---|---|---|---|---|
| MABC | **2.9031** | **2.9572** | **2.9317** | **0.0203** | 1.18*h* |
| ABC | 3.1283 | 3.7683 | 3.3069 | 0.2642 | **1.17*h*** |
| GA | 13.0426 | 17.1413 | 15.1218 | 1.6347 | 1.24*h* |
| PSO | 3.3380 | 3.6055 | 3.4301 | 0.1022 | 1.25*h* |
| DE | 5.4189 | 6.0074 | 5.7244 | 0.2277 | 1.26*h* |

## IV. Conclusion

A modified ABC algorithm (MABC) is proposed in this paper. MABC utilizes a one-position inheritance scheme and the best so-far-searched solution is used to speed up the convergence of the algorithm. The efficiency and effectiveness of MABC is showcased on the design of a loudspeaker design problem. After several hundreds of function evaluations, MABC converges faster and attains better solution than ABC, GA, PSO and DE algorithms.

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