Enhanced Artificial Immune System Algorithm and Its Comparison to Bio-Inspired Optimization Techniques for Electromagnetics Applications

Ozlem Kilic and Quang M. Nguyen

Department of Electrical Engineering and Computer Science
The Catholic University of America, Washington, DC, 20064, USA
kilic@cua.edu, 93nguyen@cardinalmail.cua.edu

Abstract **─** This paper introduces an enhanced artificial immune system algorithm (EAIS) that benefits from a hybrid approach by integrating concepts from the genetic algorithm (GA) and particle swarm optimization (PSO). The potential of the EAIS algorithm is demonstrated by comparing its performance with other bio-inspired optimization algorithms; namely the particle swarm optimization (PSO) and the conventional artificial immune system (AIS) when applied to two electromagnetics applications, such as the design of antireflective surfaces, and microstrip electromagnetic band gap (EBG) structures.

Index Terms **─** Antireflective surface, artificial immune system (AIS), bio-inspired optimization, enhanced artificial immune system (EAIS), microstrip (EBG), particle swarm optimization (PSO).

I. INTRODUCTION

Bio-inspired optimization techniques typically rely on a number of agents that simultaneously sample the optimization space in a random fashion. The process is iterated until a desired solution or the maximum number of iterations is reached. The initial step is purely random, hence requires no a-priori guess of the solution. More intelligence is added to the heuristic search at each iteration by taking advantage of the accumulated knowledge of the search domain among the agents. This intelligence is based on the computation of a cost function, which is a measure of how well each agent has performed with respect to the desired state; with high costs referring to poor solutions. The basic principles of bio-inspired optimization methods are shown in Fig. 1.

The application of bio-inspired optimization techniques to engineering problems is not a new concept. One of the well-known and original algorithms of this nature is the genetic algorithm (GA), which is based on the genetic recombination and mutation of species, [1]. Some other bio-inspired optimization techniques include the particle swarm optimization (PSO), which is inspired by the intelligent search of bees in a swarm to find the best food source in a field, [2], and the artificial immune system (AIS), which is based on the behavior of our immune system in defending our body against viruses by adapting to the optimal antibody for a given antigen, [3]. Another recent bio-inspired algorithm is the covariance matrix adaption evolutionary strategy, which was applied to the design of linear arrays in [4]. Among these methods, GA and PSO have been applied to electromagnetics problems before. However, the application of AIS in electromagnetics have been relatively scarce. Most uses for these algorithms have been in the area of networks, resource constructed scheduling, data mining, etc. [5]. Our group has investigated AIS in the context of radar absorbing material design, and multi-beam satellite antenna side lobe control in [6]. In this paper, we further enhance the AIS algorithm (EAIS) and compare its performance to the conventional AIS and PSO for antireflective surfaces, and microstrip electromagnetic band gap (EBG) structures. We show that the consistent success of the enhanced AIS algorithm makes it a promising tool for the electromagnetics community.

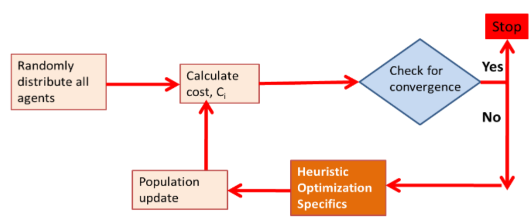

Fig. 1. A general block diagram of bio-inspired optimization methods.

The rest of the paper is organized as follows. Section 2 describes the principles of EAIS. Section 3 investigates the performance of AIS, PSO and EAIS when they are applied to electromagnetics designs. Finally, Section 4 concludes the paper.

II. ENHANCED ARTIFICIAL IMMUNE SYSTEM ALGORITHM (EAIS)

The conventional AIS optimization is based on the clonal selection principles of our immune system

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response to potential disease generating metabolisms, and simulates human body's defense system against viruses. Our adaptive immune system produces antibodies whose purpose is to bind to any antigen that it recognizes. For engineering applications, antibodies represent a possible solution to the optimization problem. The optimization space is discretized in order to emulate the binary form of gene behavior. The generic "Heuristic Optimization Specifics" step shown in Fig. 1 is replaced by four steps in AIS: cloning, mutation, combination and sorting as shown in Fig. 2.

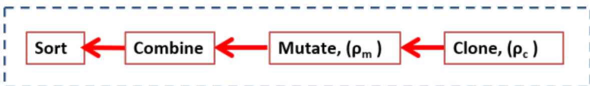


Fig. 2. Conventional AIS procedure steps.

In challenging problems, AIS can reach a state of stagnation where all good solutions in the set may differ by only a few bits [6]. In this paper, we incorporated modifications to the conventional AIS algorithm to improve its performance by bringing more intelligence to the mutation stage as well as by introducing concepts from other evolutionary algorithms. The EAIS specific procedures are shown in Fig. 3, where the dark shaded boxes indicate new steps to the process, and the light shade for the mutation step indicates a modification.

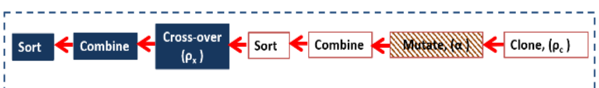


Fig. 3. Enhanced AIS procedure steps.

We modify the heuristic optimization specifics in AIS by modifying the mutation concept, and introducing a cross over operation. We also revise the population update process. The mutation stage benefits from the velocity and position update mechanism of PSO. The new cross over stage enhances the randomness using concepts from GA. Finally the population update stage utilizes PSO's global memory principles. The details of each enhancement stage are provided as follows.

(i) Mutation Stage Enhancements

Mutation enables AIS to randomly explore the search space by allowing it to move out of a local optimum and avoid stagnation. The conventional AIS algorithm carries this out by randomly flipping a certain number of bits in the solution set. The only intelligence incorporated in the conventional AIS at this stage is the number of bits to be flipped, with good solutions going through fewer flips than poor solutions. The proposed enhancement introduces a process similar to the velocity update mechanism of the PSO, where the bees get pulled towards the global best value. The value of the new antibody Ab^* after the mutation process is computed as in Equation (1):

$$Ab^* = Ab + \alpha \times rand \times Ab + \alpha \times rand \times (Ab - Ab_{best}), \quad (1)$$

where Ab_{best} is the value of the best solution in the set, Ab is the value before mutation, and α is the mutation rate which exponentially varies as a function of the rank of the antibody, i.e., $\alpha = e^{-1/k}$ and *rand* is a random number between [0-1]. This process influences the mutation towards the best solution in the set, [7].

(ii) Crossover Stage Enhancements

Crossover is a process where a new binary set is produced from the existing set by randomly combining portions from different solutions. It is used in GA to create "children" from "a parent." This concept is applied to EAIS to create a new set of antibodies by crossing the antibodies created as a result of the cloning and mutation stages. The modified algorithm selects the top N_β antibodies from the output of the conventional AIS, i.e., the combined set of cloning and mutation operations. Each antibody is split into 2 segments. The number of bits in each segments is defined by the user, based on the cross-over split ratio $n_1 : n_2$ where n_1 denotes the number of bits with the most significant bits in the string, and n_2 denotes the number of remaining bits. The two segments are randomly crossed among each other to create a new set of N_x antibodies, where $N_x = \rho_x \times N_a$ is the size of the cross-over set, and ρ_x is the cross over ratio. The concept of crossover is demonstrated in Fig. 4. Finally, the crossover set is combined with the cloned and mutated sets. The antibodies are sorted one more time with respect to their cost values. The top N_a antibodies are selected from this set to start over again.

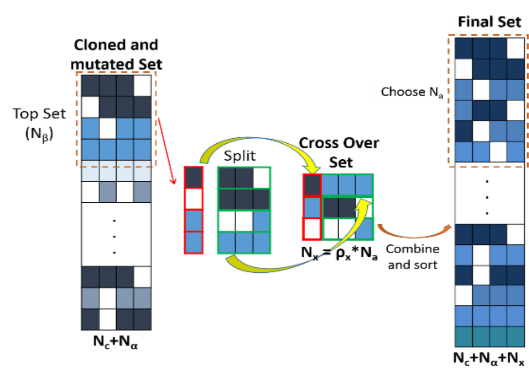


Fig. 4. Crossover concept of EAIS.

(iii) Population Update Stage Enhancements

At this point, the original population has been replaced with the new set of (N_a) antibodies utilizing cloning, mutation and cross over. The AIS algorithm can continue to iterate these steps to search for the solution. In challenging problems, AIS can reach a state of stagnation where all good solutions in the set may differ by only a few bits. Another enhancement inspired by PSO is implemented at this stage. The solution set of N_a antibodies is split into three sets for separate treatments. The top few solutions from Set 1 are kept in order to remember the best solutions achieved. This is similar to the group memory concept in PSO in the context of the global best term. The rest of the antibodies are divided into two groups, i.e., Sets 2 and 3. Antibodies in Set 2 are replaced by a local random search in the vicinity of the best solution. Set 3 is replaced by a global search carried out randomly in the entire optimization space. The range of the local search can be adjusted dynamically to focus more in the vicinity of the best solutions as the number of iterations increase. The concept of these three sets and how they are treated are shown in Fig. 5. For the local search in Set 2, the approach is to utilize PSO with only a few agents and for a few iterations. The remaining solutions in Set 3 are simply replaced randomly. It should be noted that the cost function computation time is the dominant term for these random search optimization algorithms. Thus, for an equivalent problem; i.e., the same number of cost function calls per iteration, EAIS computation time is similar to AIS regardless of the few extra steps added.

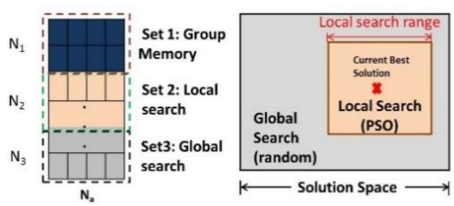


Fig. 5. Population update process of EAIS.

III. APPLICATION TO ELECTROMAGNETIC PROBLEMS

A. Antireflective Surface (AR) design

The first application we consider addresses an anti-reflective surface design, which is useful for both military (e.g., camouflaging) and commercial applications (e.g., efficient collection of energy such as in microwave or millimeter wave lenses). The design is inspired by the moth-eye structure, which consists of multiple layers of periodic gratings that enable the absorption of light at a wide range of incidence angles, [8]. In our application, we use a dielectric slab with an inverse moth eye pattern (i.e., holes rather than protrusions) applied to both top and bottom surfaces of the structure. We use the rigorous coupled wave algorithm (RCW) to simulate the model. Our goal is to achieve a desired total reflection coefficient of $\Gamma \le -30\,dB$ within the Ka-band over the 32-38 GHz bandwidth.

The design has an infinitely thick (i.e., half space) substrate with a dielectric constant of $\varepsilon_r = 2.56$, and an index of refraction of $n_s = 1.6$. The holes are backfilled with air, $n_h = 1$ and the grating period, Λ, is fixed at 3.1 mm, as depicted in Fig. 6. The grating heights, h_1 and h_2, and the hole diameters, d_1 and d_2, are the variables of the design. The incident field is assumed to be a TE polarized plane wave obliquely incident on the surface. The cost function of EAIS is defined as the square of a difference between the desired criteria and the reflection coefficient. The parameters of the optimization algorithms are summarized in Table 1.

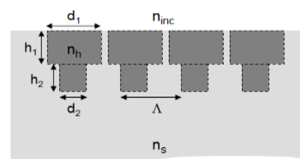


Fig. 6. Inverse half space AR surface design.

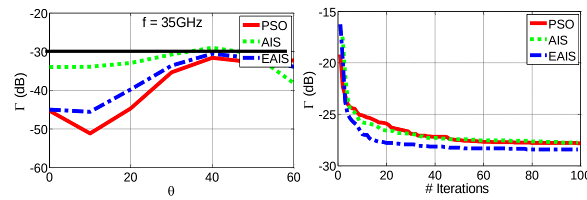
Table 1: Algorithm parameters for AR surface design

	PSO	AIS	EAIS
	$c_1 = c_2 = 1$	$\rho_c = 0.6$ $\rho_m = 0.5$	$\rho_c = 0.6,\ \rho_x = 1$ $n_1 / n_2 = 0.2$
N_a	96	28	18
N_b	n/a	12	12

The bandwidth was sampled in steps of 1 GHz. The best solution achieved at the end of 100 iterations is shown in Table 2 along with the best minimum reflection coefficients over the 32-38 GHz bandwidth. The optimized reflection coefficients is plotted in Fig. 7 (a) as a function of the incidence angle at the center frequency, i.e., f = 35 GHz for the three algorithms. We observe that for this particular angle, AIS does not converge at $\theta = 40^0$. Also, overall it is evident that PSO has reached a better solution for a wide range of incident angles. However, it should be noted that achieving a value better than the desired criteria, i.e., $\Gamma \le -30\,dB$, is not part of the objectives for any of these algorithms, i.e., each algorithm accepts any value of $\Gamma \le -30\,dB$ as a converged solution. From the perspective of the rate of convergence, EAIS performs the best as shown in Fig. 7 (b), where Γ is plotted against the number of iterations.

Table 2: AR surface design solution

AR Design	PSO	AIS	EAIS
h_1 (mm)	2.58	2.67	2.60
h_2 (mm)	1.82	1.74	1.80
d_1 (mm)	3.02	3.01	3.02
d_2 (mm)	2.15	2.09	2.15
Γ (dB)	-28.62	-28.52	-28.62



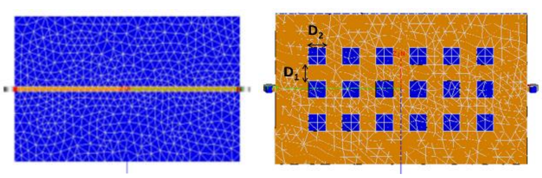
(a) (b)

Fig. 7. Optimized AR surface design at f = 35 GHz and performance of three algorithms.

B. Microstrip EBG structures

In this application, we design a low pass filter operating at [4-7.5 GHz] such that $S_{21} \geq -5$ dB across [4-6 GHz], and $S_{21} \leq -25$ dB over [6.5-7.5 GHz]. To achieve the performance, we consider a 50 Ohm microstrip line symmetrically residing on a periodically etched ground plane, where 50 mil thick, 2.33x1.53 inches RT/Duroid 6010 ($\varepsilon_r = 10.2$) is used as the substrate. To model the structure, we use EM commercial software, FEKO, which is based on the Method of Moments (MoM).

The simulated model for our design is shown in Fig. 8. The optimization variables; i.e., D_1 and D_2 are set to be between 50-250 mils. The optimization parameters used for each algorithm are summarized in Table 3. The solution achieved by each algorithm is summarized in Table 4, and the achieved performance is plotted in Fig. 9. We observe that, all three algorithms converge to similar solutions. A plot of the best cost versus the number of iterations is shown Fig. 9 (b). Although EAIS reaches the vicinity of the desired solution fastest, PSO achieves the best cost in the end.



(a) Top view (b) Bottom view

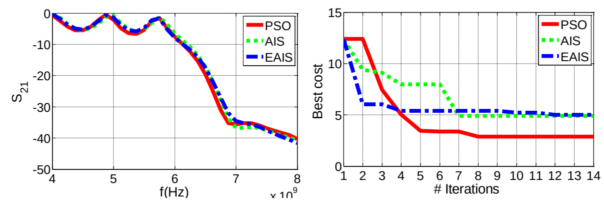
Fig. 8. Microstrip EBG line with etched squares in the ground plane.

Table 3: Algorithm parameters for microstrip EBG

	PSO	AIS	EAIS
N_a	10	4	2
N_b	n/a	12	12
# Cost computations/iteration	10	10	10
N_{max}	14	14	14

Table 4: Microstrip EBG design solution

	PSO	AIS	EAIS
D_1 (mil)	50	55	58
D_2 (mil)	222	216	213



(a) (b)

Fig. 9. Optimized microstrip EBG structure and performance of three algorithms.

IV. CONCLUSION

The robustness of the EAIS algorithm was demonstrated in comparison to PSO and AIS as they were applied to two electromagnetics applications; antireflective surface design using RCW, and microstrip electromagnetic band gap structure using MoM. EAIS consistently performed more robust than the other two algorithms. While it can never be claimed that a particular random search algorithm will always perform better than others, as the nature of a problem might fit the principles of an algorithm better at times, EAIS was shown to be consistently robust presenting itself as a viable tool for challenging electromagnetics problems.

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