Biologically Inspired Optimization of Antenna Arrays

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Abstract **─** Modeling biological evolution on a computer began in the 1960s with evolution strategies in Europe and genetic algorithms in the United States. Genetic algorithms were introduced to the antenna community in the early 1990s. Since that time, they have become ubiquitous in computational electromagnetics and standard options on commercial software packages. Other biological design methods based upon biological processes in nature have also been introduced. This article provides an introduction to genetic algorithms, particle swarm optimization, and ant colony optimization. Several examples of antenna array optimization are presented to illustrate the power of these algorithms.

Index Terms **─** Ant colony optimization, antenna arrays, genetic algorithms, numerical optimization, particle swarm optimization, phased arrays.

I. INTRODUCTION

Modeling biological evolution on a computer started in the 1960s when Rechenberg [1] introduced evolution strategies while Holland [2] introduced genetic algorithms. Evolutionary algorithms with real-valued solutions had a parent and a mutated version of a parent. Genetic algorithms with binary encoded solutions used populations of variables and crossover between variables to add variety. Goldberg [3] launched global optimization into the mainstream through applications of genetic algorithms to practical problems.

Antenna applications of genetic algorithms began in the early 1990s [4]. Since that time, thousands of papers and some books have been written about antenna optimization using a genetic algorithm [5], [6]. Later in the 1990s, other biologically inspired approaches to random optimization appeared. The antenna community quickly picked up on these algorithms and tackled optimization with a new flare. All of these algorithms are random searches with the ability of jumping out of local minima in an effort to find the global minimum. In spite of the claims that one random search algorithm is better than another, the No Free Lunch (NFL) theorem says that the computational cost of finding a solution for a class of mathematical problems is the same for any random search algorithm when averaged over all problems in the class. Thus, tweaking the parameters of one algorithm can cause it to outperform another algorithm for a handful of problems but not for all problems.

This paper presents three antenna array optimization applications that are solved using three different global search algorithms. We do not advocate one algorithm over the other because of the NFL theorem. These algorithms do not guarantee the "best" solution, but they usually find very good solutions that meet specifications.

II. GENETIC ALGORITM

The inspiration for the Genetic Algorithm or "GA" came from genetics and natural selection [7]. The GA starts with a list of randomly generated solutions. The list is called the population and each solution is an individual or

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chromosome. The original GAs, had the solutions encoded into binary, but today both binary and continuous GAs are used [8]. Each solution is evaluated by the objective function output. Maximization problems have a fitness while minimization problems have a cost. Those chromosomes with a low fitness are discarded, while those with a high fitness are retained in the population (natural selection). The most fit chromosomes have the highest probability of mating or combining chromosomes in such a way as to create new chromosomes or offspring that replace the chromosomes discarded in natural selection. Finally, chromosomes in the new population are mutated (randomly changes made to the chromosome). The fitness of this generation is evaluated, then a new generation begins with natural selection. This process continues until a suitable solution is found.

In our first example of using biologically inspired algorithms to optimize antenna arrays, we use the binary GA to design a dynamically thinned array that suppresses sidelobe interference [9]. Each element can be either connected to (i.e., element is on) or disconnected from (i.e., element is off) the beam forming network by means of a switch (Fig. 1). The GA maximizes a quantity that is proportional to the Signal-to-Noise plus Interference Ratio (SINR) by determining the best configuration for the switches.

Consider a uniform array of 64 half-wavelength spaced elements. The interference configuration is supposed static with two interfering signals impinging on the antenna from $\phi_1 = 42^\circ$ and $\phi_2 = 113^\circ$, while the desired signal arrives from broadside ($\phi = 90^\circ$). The power of each interfering signal is 30 dB above that of the desired signal, while the background noise contribution is negligible. The values of the fitness function, defined according to [10], and of the SINR are shown in Fig. 2 (a) for the best individual (i.e., solution) of the GA population for each generation throughout the optimization process. It is worth noting how the SINR increases generation after generation starting from very low values close to -5 dB up to almost 25 dB. This is achieved through the generation of deeper and deeper sidelobe nulls in the interference directions. In particular, Fig. 2 (b) shows the depth of the nulls in the directions of the two interferences for each generation. Although the fitness always stays the same or goes up, the null depths can go up, stay the same, or go down with each generation. One null may go down a lot while another null may go up, but on the average, the SINR goes up.

The array factor and the corresponding on-off configuration of the switches obtained by the best solution of the GA optimization at the end of the optimization are shown in Figs. 3 (a) and 3 (b), respectively. It is evident in Fig. 3 (a) that the GA is effective in suppressing the interferences by placing deep nulls in the sidelobe region in their directions of arrival.

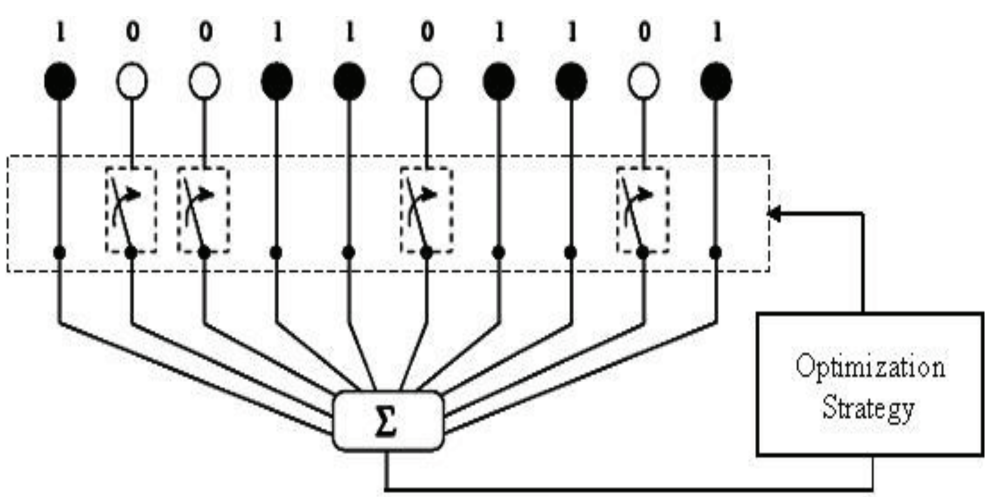
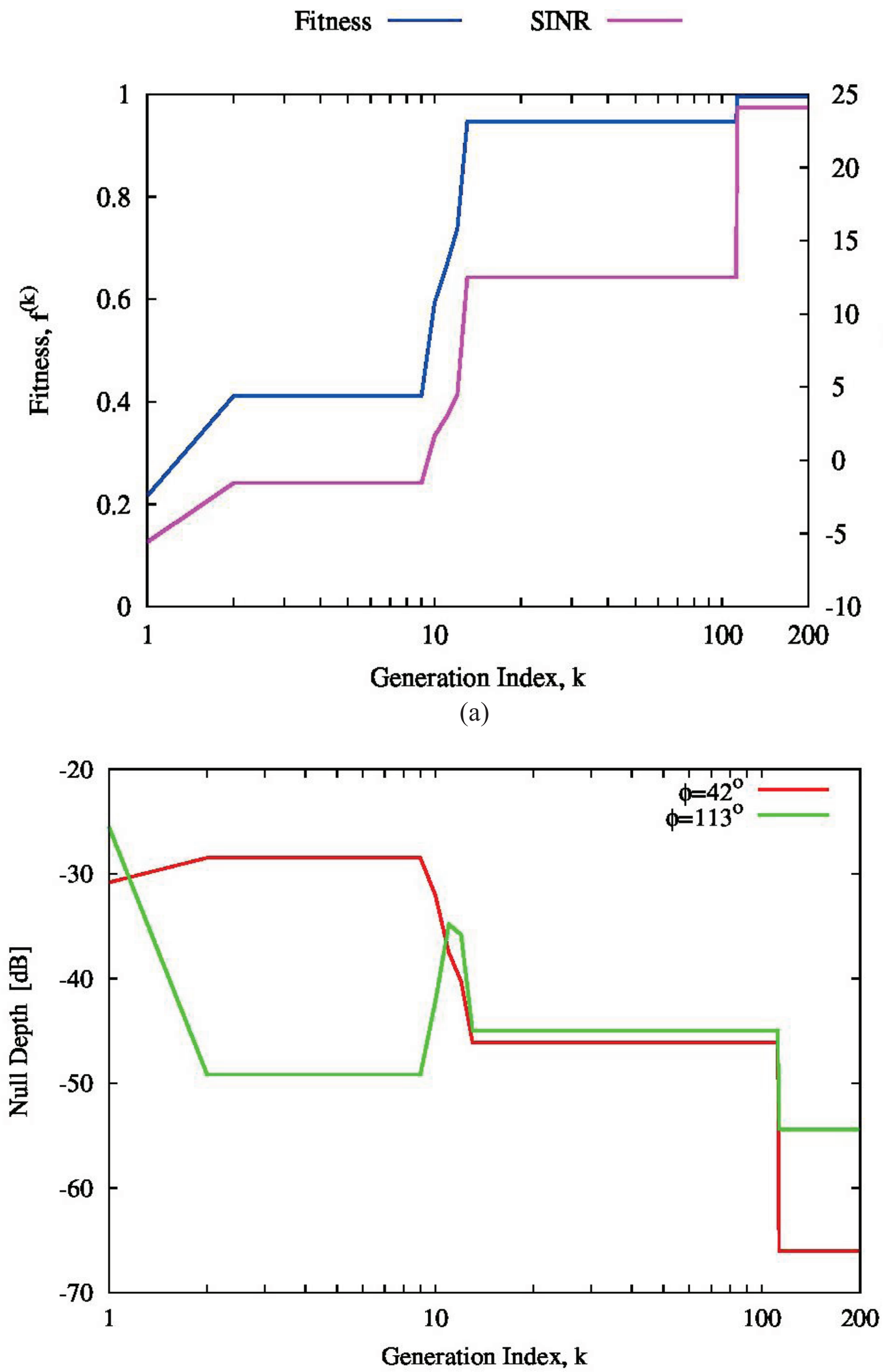


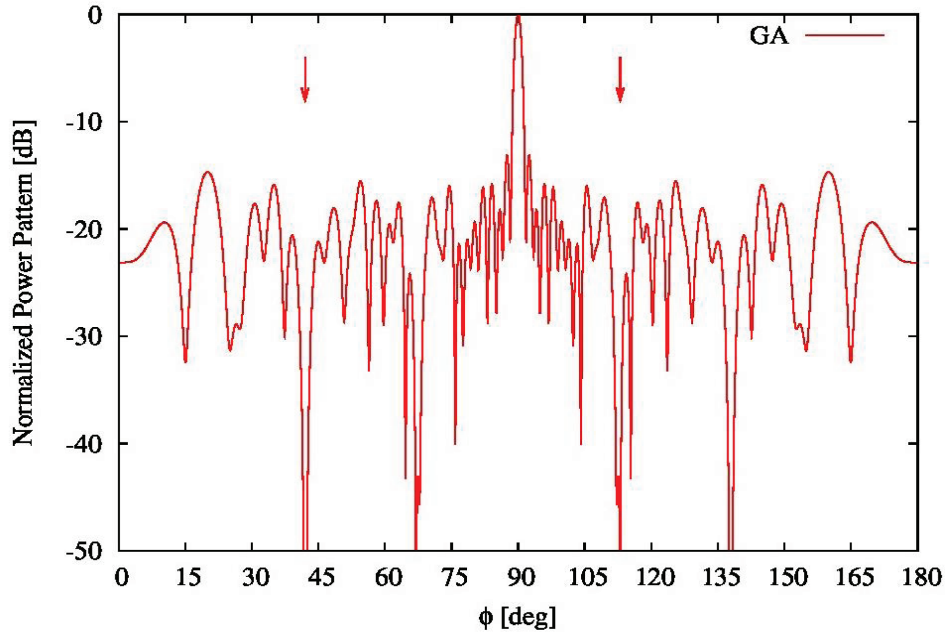
Fig. 1. Sketch of a dynamic thinned array.



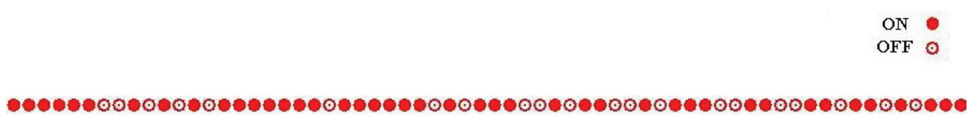
(a)

(b)

Fig. 2. Behavior: (a) of the fitness function and of the SINR for the best solution defined by means of the GA, and (b) of the null depths in the directions of the interferences versus the iteration index.



(a)



(b)

Fig. 3. Plot: (a) of the power pattern with arrows along the interference directions, and (b) of the on-off configuration of the switches for the best solution of the GA optimization at the final generation.

III. PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) models the swarming or flocking animals and their motion [11][12]. PSO has a random population matrix like the GA, but the rows in the matrix are called particles instead of chromosomes. Particles are potential solutions that move in a particular direction on the cost surface with a certain velocity. Particles update their positions and velocities using formulas based on the knowledge about the best solution achieved by each particle in its movements (i.e., personal best) and by the complete swarm of particles (i.e., global best).

Our second example applies PSO to optimize the design of a Time-Modulated Linear Array (TMLA) [13], allowing the generation of multiple beam patterns on receive. As for the antenna architecture of a TMLA, it is very similar to that of the thinned array shown in Fig. 1. Unlike thinned arrays, in TMLAs the switches are periodically turned on and off by means of proper time switching sequences such that the average harmonic patterns generated within the modulation period are characterized by user-defined properties [13].

The example TMLA has 16 elements with half-wavelength spacing. The goal is to simultaneously generate sum and difference patterns using the first (h=1) and central (h=0) harmonic radiation patterns. The two beam patterns must have the minimum Sidelobe Level (SLL) of the secondary lobes. Furthermore, the level of the higher harmonic terms (h>1), the so-called Sideband Level (SBL), generated by the periodic time-modulation of the switches should be as low as possible. Towards this aim, the cost function is defined according to the guidelines of [13].

The array patterns of the best solution are shown in Fig. 4. Figure 4 (a) shows the difference and sum patterns generated by means of the TMLAs at the central (h=0) and first (h=1) harmonic radiation when controlling the switches according to the on-off configuration of Fig. 4 (b). In Fig. 4 (b), the bars represent the instants when the elements are on while the elements are disconnected from the feeding network in the remaining part of the modulation period.

Figure 5 (a) is a graph of the different components of the cost function, related to the SLL at both h=0 and h=1, and of the SBL, as well as the cumulative cost function values for the best solution of the PSO at each iteration. SLLs of -17 dB are achieved for both power patterns [Fig. 4 (a)] and the SBL of the higher harmonics is effectively suppressed for h>1 [Fig. 5 (b)]. The percentage of power, with respect to the total, associated to the pattern at the central and first nine harmonics is shown in Fig. 6. It is possible to observe that the largest amount of power is used for the sum and difference patterns at h=0 and h=1, while the power gets quickly to zero for higher harmonic modes.

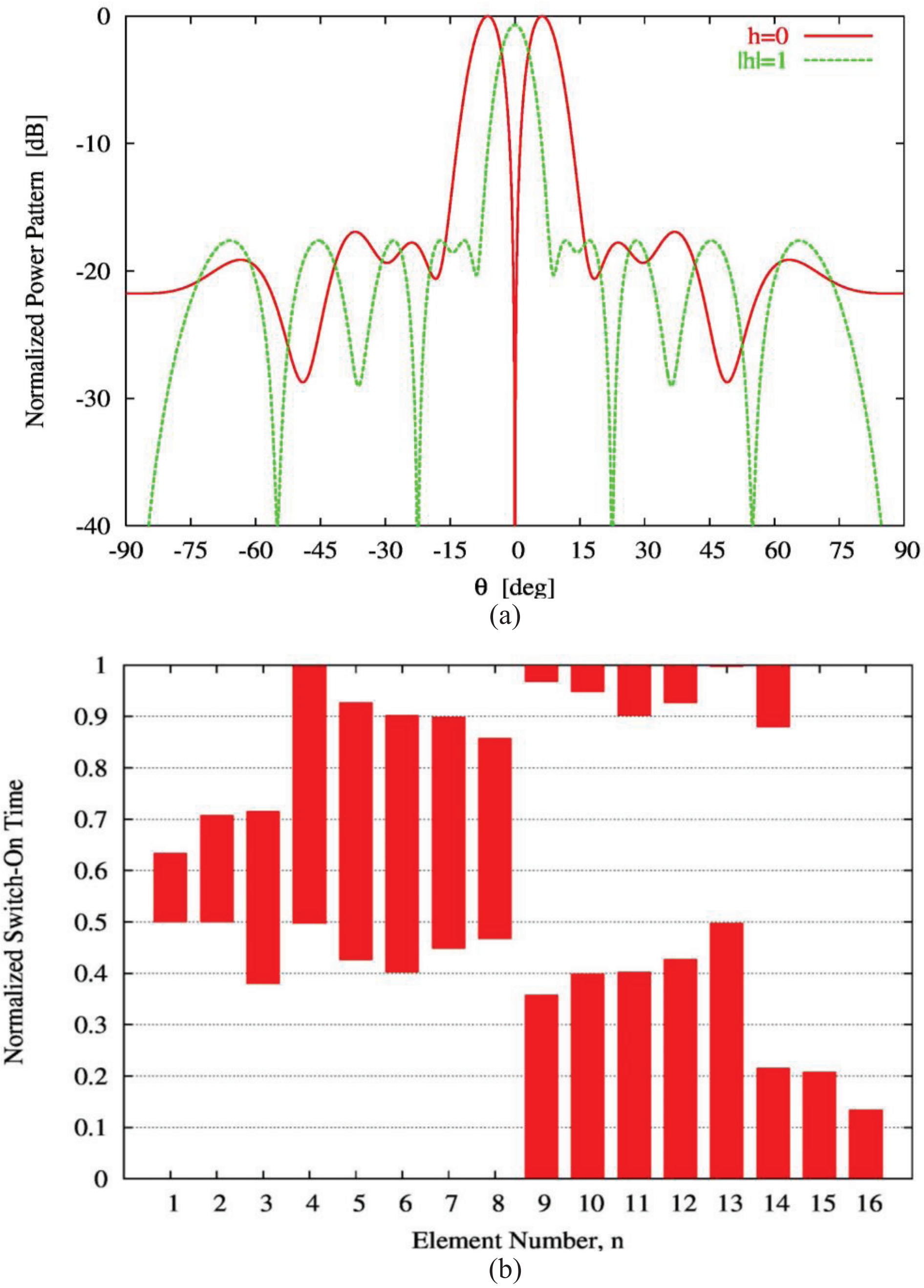


Fig. 4. Plot: (a) of the power patterns generated by the TMLA for h=0 and |h|=1, and (b) of on-off time-modulation sequence for the best solution of the PSO optimization at convergence.

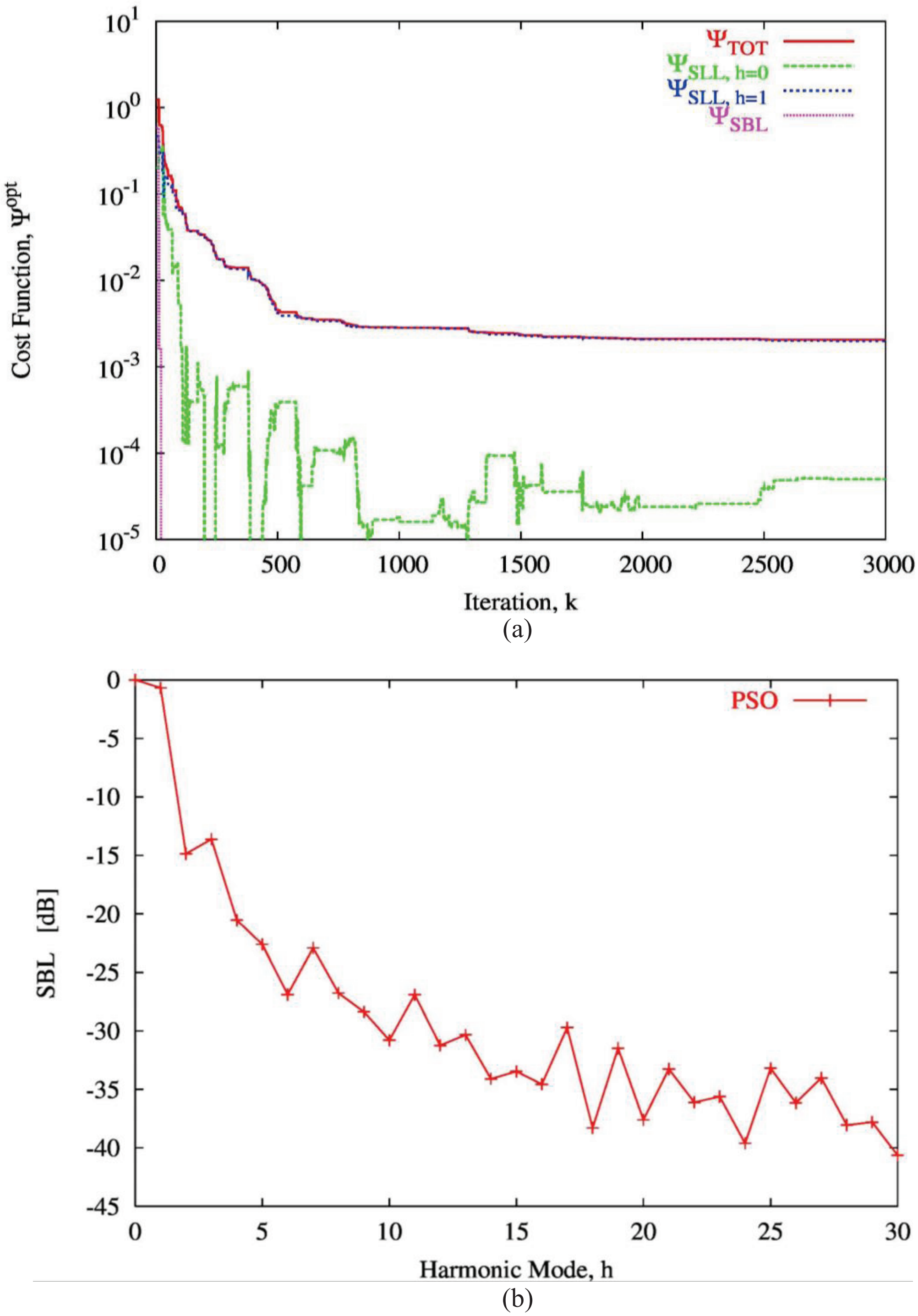


Fig. 5. Behavior: (a) of the cost function terms and of their sum for the best solution defined by means of the PSO versus the iteration index, and (b) of the SBL as a function of the harmonic index.

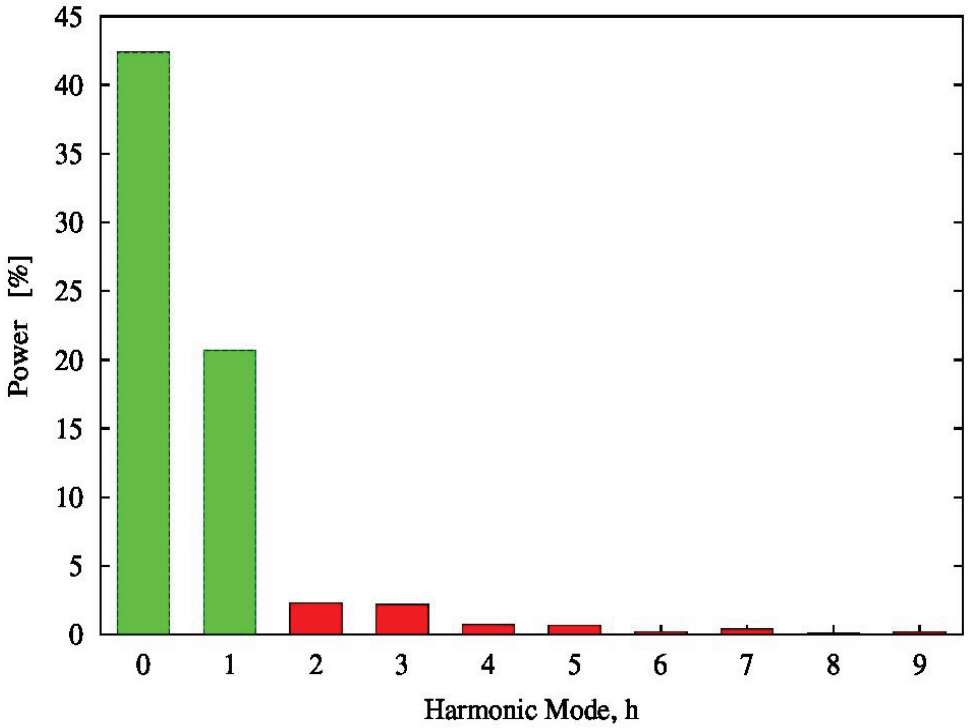


Fig. 6. Percentage of individual power associated to the harmonic radiations.

IV. ANT COLONY OPTIMIZATION

Ant Colony Optimization (ACO) is based on the behavior of ant colonies in obtaining food and carrying it back to the nest [14]. When ants search for food, they emit a pheromone (chemical) along their trail. Other ants follow the pheromone path to the food while laying down more pheromone. Shorter paths to the food result in stronger trails of pheromone, because the pheromone evaporates with time. Stronger pheromone paths are also the shortest paths, so they attract more ants an eventually, the shorter path dominates. When the food source is gone, the pheromones gradually evaporate, and ants no longer follow that path.

A traveling salesperson problem is perfect for ACO, because this problem closely resembles finding the shortest path to a food source. ACO results in premature convergence to a local optimal solution unless pheromone evaporation is implemented; a solution disappears after a period of time. As a result, the pheromone along the best path found so far by the algorithm is given some weight in calculating the new pheromone levels.

The design of a sub-arrayed antenna array generating an optimal sum pattern through a set of independent and optimal weighting coefficients and a compromise/sub-optimal difference pattern by aggregating the array elements into sub-arrays and defining suitable sub-array weights is addressed by means of the ACO. A sketch of the antenna configuration appears in Fig. 7, where only half array is shown due to symmetry.

Exploiting the theoretical guidelines of [15], it has been shown that the problem can be defined as an excitation matching problem, where the excitations of the compromise difference pattern can be obtained by approximating the values of a set of excitations generating an optimal difference power pattern. Moreover, the solution space can be represented in this case by means of a binary tree [Fig. 8 (a)], where each path identifies a possible sub-array configuration and the corresponding set of sub-array weights. Accordingly, the goal is to find the sub-optimal difference pattern closest to the optimal one. Besides the ad-hoc local optimization technique originally proposed in [15], called Border Element Method (BEM), the ACO has been adopted [16] and has showed superior performance thanks to the fact that it can avoid local minima. In this case, the ants leave pheromone on the edges of the binary tree proportionally to the suitability of the solutions obtained at the previous iteration. As a representative example, Fig. 8 (b) shows the pheromone level, higher where the lines are ticker, left by the ants of the colony on the edges of the binary tree. At the next generations, the ants will choose with higher probability paths/solutions with more pheromone.

Our final example is a 40 element array with 4 sub-arrays in each half of the array. The reference/optimal excitations are chosen to generate a Zolotarev difference pattern with SLL=-30 dB. The best solutions obtained by means of the ACO is shown in Fig. 9, together with the one achieved through the BEM. As a first observation, it is possible to note that the compromise pattern synthesized with the ACO is closer to the reference one than the BEM pattern. This fact is confirmed by the values of the cost function of Fig. 10. The fitness of the BEM oscillates as it converges. After 100 iterations, the BEM seems to be stuck in a local minimum, while the average ACO run has found a much lower minimum.

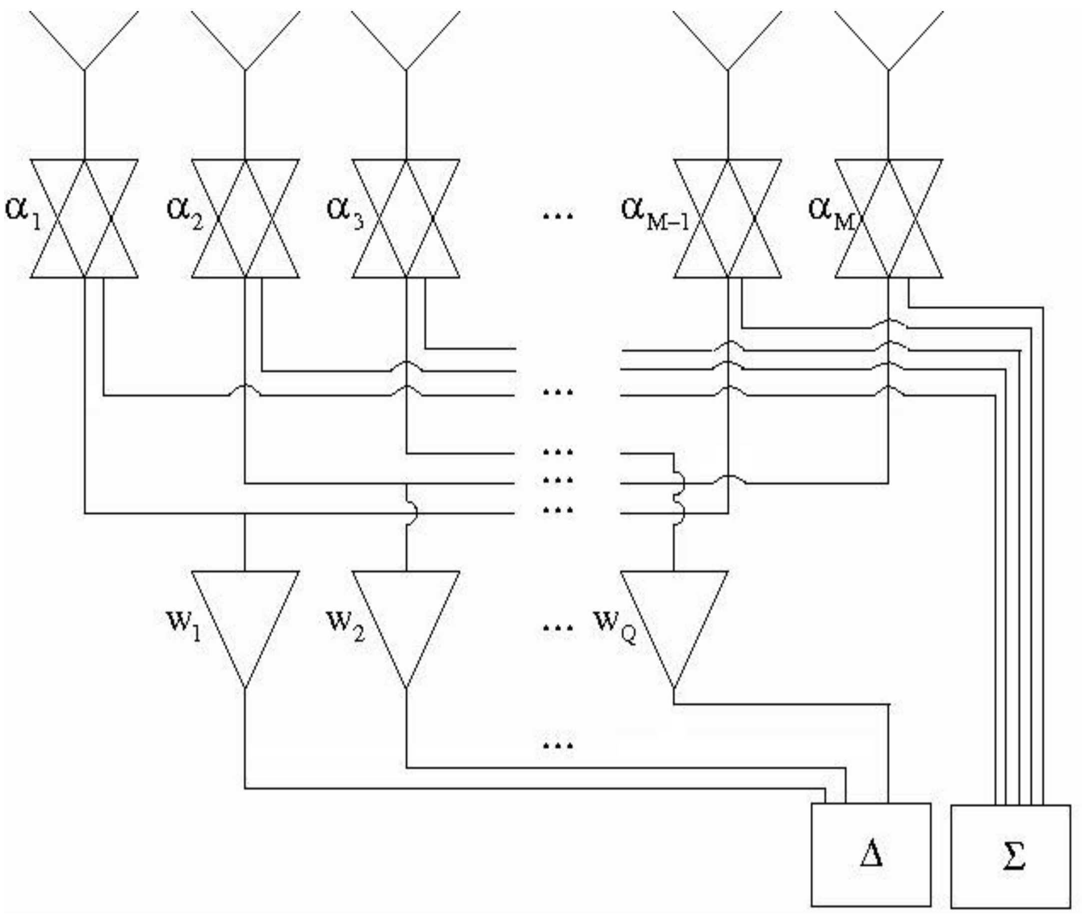


Fig. 7. Sketch of a compromise sub-arrayed array.

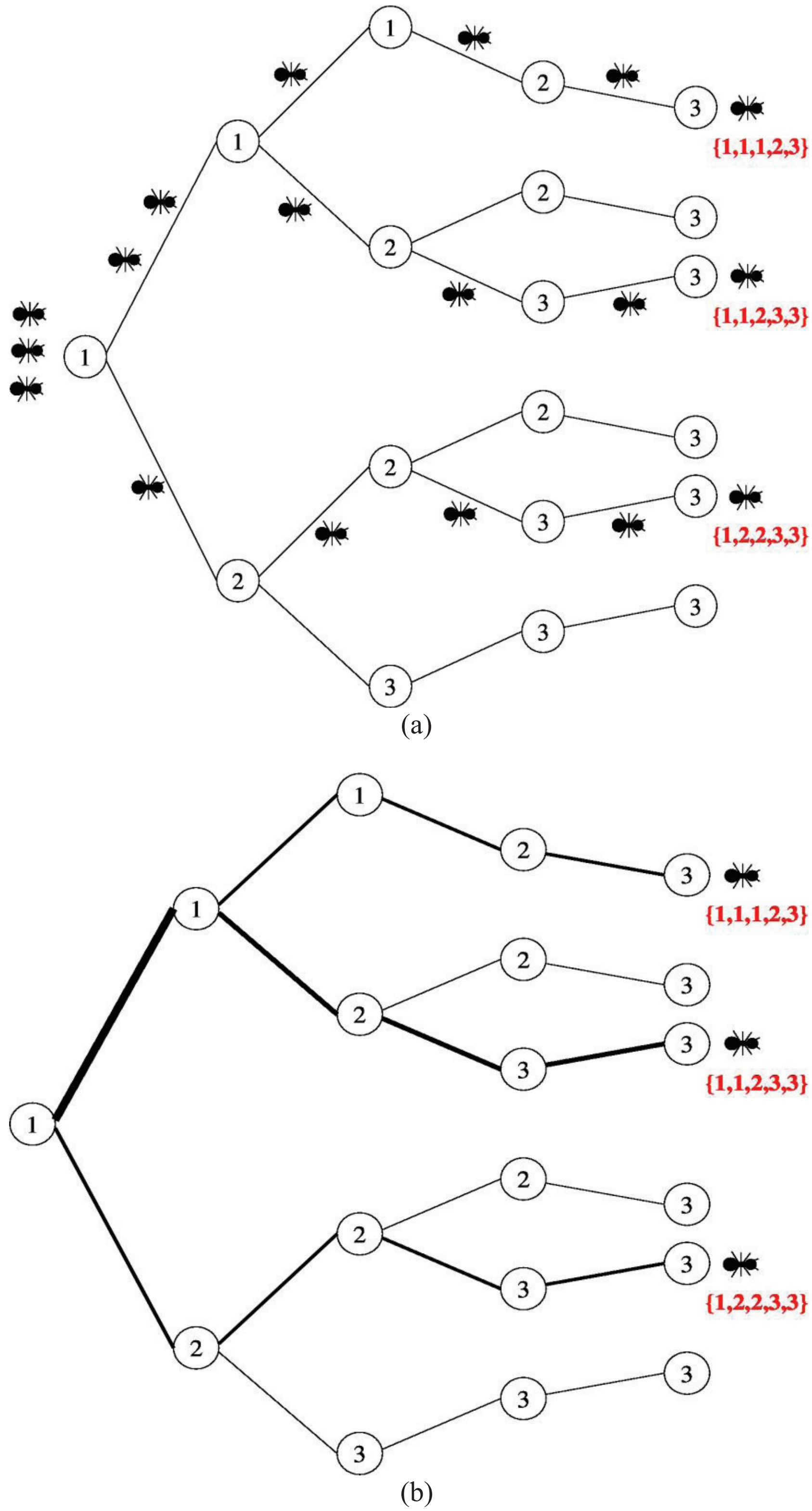


Fig. 8. Sketch: (a) of the solution tree where each ant defines a trial sub-array configuration whose sub-array weights are computed as in [15], and (b) of the solution tree with updated levels of pheromone left on the edges from the ants.

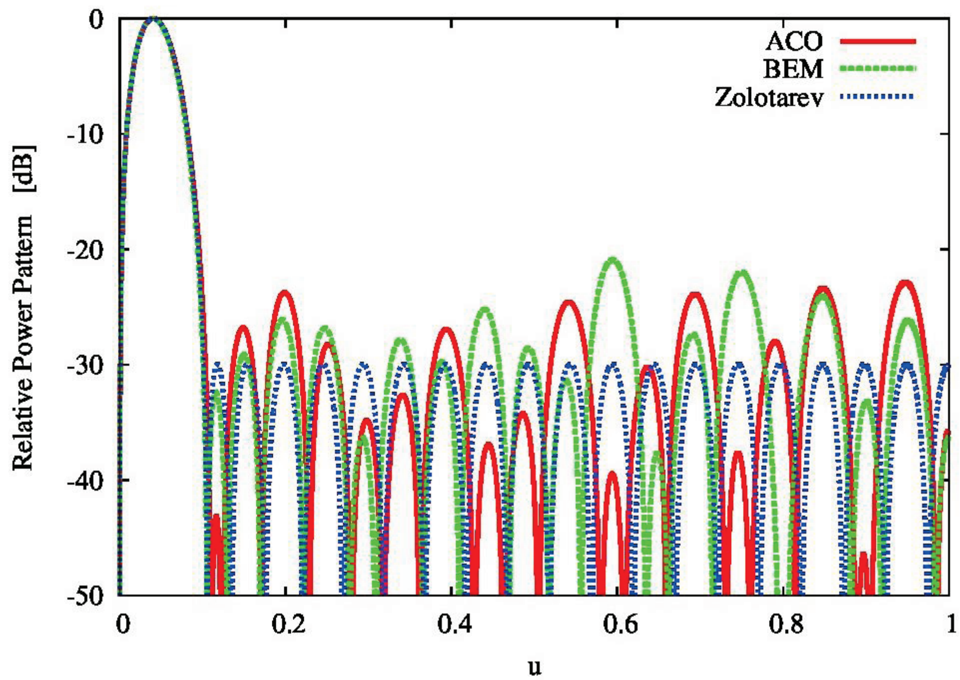


Fig. 9. Plot of the reference power pattern (Zolotarev) and of the compromise power patterns synthesized with the ACO and the BEM.

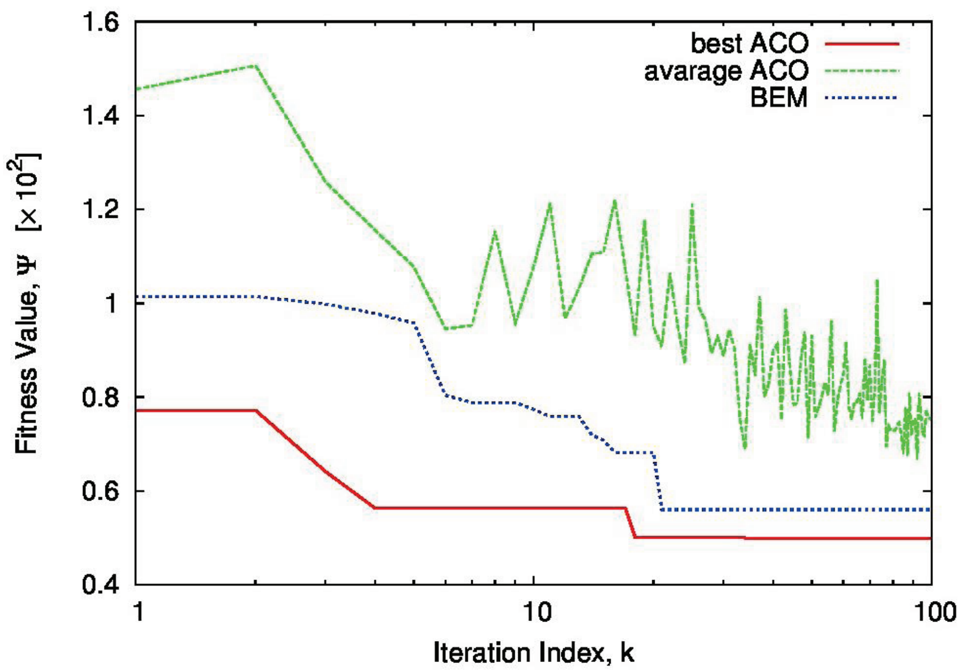


Fig. 10. Behavior of the cost function versus the iteration index for the best solution of the ACO and the average of the ACO colony and for the BEM.

VI. CONCLUSIONS

This paper presented three different biologically based numerical optimization strategies and applied each approach to an antenna array design problem. GA, PSO, and ACO are all random search algorithms that are guided by biological principles. Table 1 lists the major terms associated with each of these algorithms. They all maintain a collection of possible solutions and use biologically based rules to search the objective function space for the best solution. The flowcharts for these algorithms are very similar as shown in Fig. 11. They are all very parallel in nature in that many individual evaluations can be done simultaneously. This parallelism was not a strong point of some other well-known global optimizations approaches, such as simulated annealing and evolutionary strategies.

Which algorithm should you use? The ACO is primarily designed for traveling salesman type problems (i.e., optimization problems where the solution space can be represented through a graph), so it is not as universally applicable to antenna design. Both GA and PSO have yielded excellent results in computational electromagnetics, although the PSO have been mainly used for the optimization of real-valued parameters over continuous spaces while the GA has binary, integer, and continuous versions [17]. We do not advocate one over the other, and the NFL theorem backs our decision.

Table 1: Terms for GA, PSO, and ACO

	GA	PSO	ACO
Solution matrix	Population	Swarm	Colony
Individual solution (Phenotype Space) [1]	Individual	Particle	Ant
Individual solution (Genotype Space)	Chromosome	Position	Path
Best solutions	Parent	Current position	Current path
New solution	Offspring	Next position	Next path
Iteration	Generation	Generation	Generation
Objective function evaluation	Fitness/cost	Fitness/cost	Desirability/cost

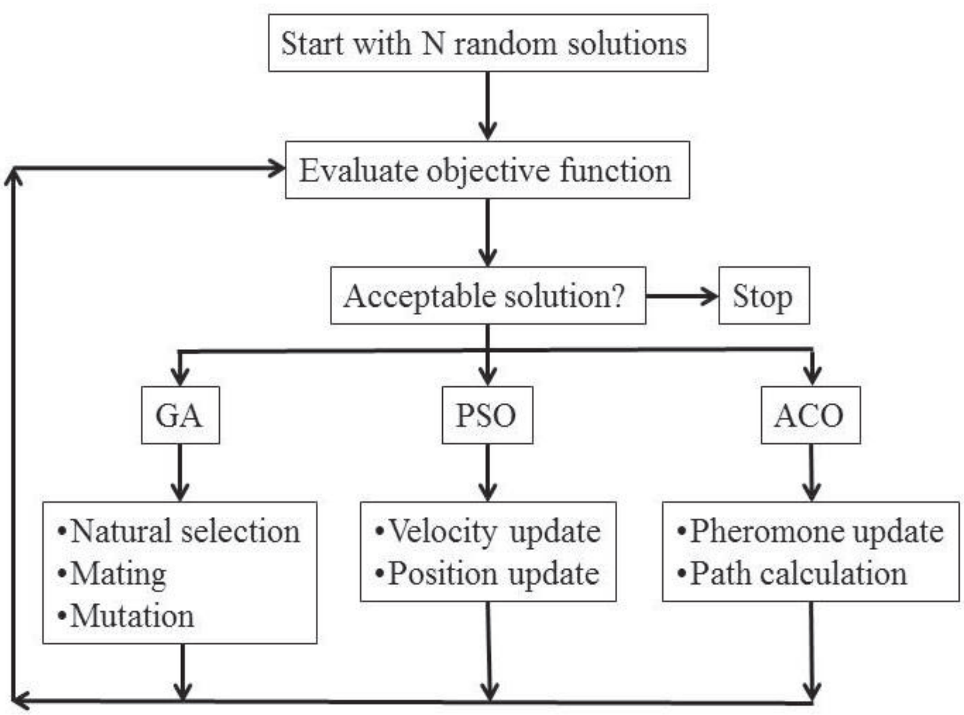


Fig. 11. Flowchart for biological optimization algorithms.

[1] The phenotype space is the space of the input parameter as they appear in the "real world," while the genotype space is the work space of the coded parameters.

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