APPLICATION OF ANT COLONY OPTIMIZATION BASED ALGORITHM TO SOLVE DIFFERENT ELECTROMAGNETIC PROBLEMS

Óscar Quevedo-Teruel and Eva Rajo-Iglesias

Universidad Carlos III de Madrid, 28911 Leganés-Madrid, Spain
oquevedo@tsc.uc3m.es, eva@tsc.uc3m.es

ABSTRACT

The aim of this work is to show the use of a well-known type of evolutionary computation optimization technique, the Ant Colony Optimization (ACO), in order to solve different electromagnetic problems: array synthesis both linear and planar and with different design criteria, design of a monopolar Ultra Wide Band (UWB) microstrip antenna and reduction of E-plane mutual coupling in a multilayer patch antennas array. To this aim, an algorithm based on the fundamentals of ACO has been developed. The algorithm uses real numbers and binary ones (depending on the structure to optimize). Some guidelines for the use of the algorithm, especially to create the desirability function, are supplied. The algorithm has demonstrated to be versatile and useful to resolve problems of different nature. Furthermore, the purpose of the work is to show (via these particular applications) the flexibility and easy implementation of this algorithm family that make it suitable to be used in most of electromagnetic optimization problems.

Key words: Ant Colony; Optimization; Monopolar UWB Antenna; EBG; Mutual Coupling; Array Design.

1. INTRODUCTION

The use of Global Search Optimization Methods to solve electromagnetic problems has been widely extended. Among them the most popular for the antenna community are Genetic Algorithms (GA) and recently Particle Swarm Optimization (PSO). Algorithms based on these methods have been used to afford the design of arrays and other types of antennas [1, 2, 3, 4, 5]. Another family of global search algorithms also based on social behaviour is the Ant Colony Optimization (ACO) that was introduced by Dorigo in 1991 and it is based on the ant colonies behaviour to obtain food and carry it back to the nest [6, 7, 8]. It has been used to solve different type of problems [9, 10, 11] employing different realizations of the algorithm. The usefulness of this optimization technique is especially powerful in distributed problems like [12, 13, 14, 15]. Although these algorithms have been applied in many different problems their use by the electromagnetic community has been limited [16, 17]. So, it is the purpose of this work to show the application of an algorithm based on ACO (using real numbers) to different antenna problems.

The paper is organized as follows. In Section 2, an overview of the basis of ACO and the implementation of the algorithm is drawn. Afterwards, three examples of design are described in Section 3. Firstly, a classical electromagnetic problem: array synthesis both linear and planar with Side Lobe Level (SLL) criteria. In all the cases, with the algorithm performance and convergence, ACO demonstrated to be as powerful as GA or PSO. Secondly, we have successfully applied the algorithm to design different monopolar Ultra Wide Band microstrip antennas. The last application was the design of a planar truncated periodic structure to reduce E-plane mutual coupling in a multilayer patch antennas array. In the last two examples we have used the *CST Microwave Studio* program as the analysis tool to calculate our ”desirability ” functions, i.e., our algorithm interacts with *CST*. Finally, some conclusions have been drawn in Section 4.

2. ANT COLONY ALGORITHM

2.1. Basis of the Algorithm

Ant Colony Optimization means algorithms based on the ant behavior in the searching for food and posterior transportation to the nest to be stored. These insects have the ability to find the “shortest path” in this task using pheromone. Some ant species use pheromone for making paths on the ground, in their way from food to the nest. This helps other ants, by sensing pheromone, to follow the path towards food discovered by other ant. Because ants deposit pheromone while walking, a larger number of ants on a path results in a larger amount of pheromone, this larger amount of pheromone stimulates more ants to choose that path and so on until finally, the ants converge to one single (short) path. Also, these pheromone evaporate with time to “delete” the path to a exhausted food source.

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2.2. Implementation of the algorithm

Imitating this behavior, optimization algorithms can be developed. In our implementation there are two main states of operation, in the first one ($forward$) the ant is looking for food whilst in the second one ($backward$) the ant has to look for the path to come back home. Then, when the ants have found the food, they have to come back to $home$, i.e. to initial positions.

ACO is discrete in nature and when it is implemented using real numbers instead of bits, a discretization of the used variables is needed. Obviously, this can affect algorithm performance in terms of the achieved solution, i.e. a smaller step could drive to better solutions (or carry the optimization scheme to the starvation) but that is not relevant for the purpose of this paper.

In a typical case we will have N variables of study so a N-dimensional space of solutions. In this case, every ant means an solution i. e. a vector with N real numbers (the values of the variables that can be changed to obtain the desired design). Every ant moves through the N-dimensional space of solutions by checking the desirability and the pheromone concentration level of all its neighboring nodes and then, making a probabilistic decision among all them. A neighboring node is calculated by changing the position of only one variable for all the parameters. This means that the ant has 2N neighboring nodes.

Paths are therefore divided into nodes and, to decide the next node the ant is going to move towards using the above mentioned rules, typically, the most extended decision criterium is the one proposed by [6] and described as:

$$p_{i,j}(t) = \frac{[\tau_j(t)]^\alpha \cdot [\eta_j]^\beta}{\sum_{l\in\theta_i}[\tau_l(t)]^\alpha \cdot [\eta_l]^\beta} \quad (1)$$

Where $p_{i,j}$ is the probability of node j to be chosen at iteration t being at node i, $\tau_j(t)$ represents the pheromone concentration associated with node j at iteration t, α ponderers the importance of pheromone concentration in the decision process whilst β does the same with the desirability, η_j is the desirability of node j, and θ_i is the set of nodes l available at decision point i.

The desirability η_j is a function that depends on the optimization goal. This function has to be evaluated at every node j for every ant. Its role is equivalent to the one of the "fitness" function in other algorithms. When the algorithm is developed the definition of this function is one of the critical issues, as in many other algorithms.

The function τ_j controls the change in the pheromone level in nodes with time. This includes the increase when ants visit that node but also the evaporation with time. The τ_j function can be implemented in different ways. In our case, we use:

$$\tau_j(t+1) = \tau_j(t) + \Delta\tau_j(t) - d(t) \quad (2)$$

Where $\Delta\tau_j(t)$ is the pheromone addition on node j, and $d(t)$ is the pheromone persistence:

$$d(t) = \begin{cases} \rho & \text{if } \operatorname{mod}(\frac{t}{\gamma}) = 0 \\ 0 & \text{if } \operatorname{mod}(\frac{t}{\gamma}) \neq 0 \end{cases} \quad (3)$$

Where γ is the period of pheromone elimination, and ρ is the coefficient of pheromone elimination by period.

The choice of the values of γ and ρ parameters is critical to achieve good results. These values have been selected empirically as $\gamma = 20$, $\rho = 1$. Also, it has been defined as $\Delta\tau_{i,j}(t) = 1$ when an ant goes to the node j from any i node. On the other hand, the parameters α and β have been selected differently for each example depending on the optimization goal.

Obviously, the value of $\Delta\tau_{i,j}(t)$ and the parameters γ and ρ are related with α, because they give the magnitude of the element ($\tau_j(t)$) that is raised to the power of α (Equations 1, 3 and 2).

As β is related with the importance of the desirability in the decision process whilst α does the same but with the pheromone concentration effect, for every example β has been chosen much more larger than α in order to increase the influence of the better solutions over the pheromone concentration (that would fix strict ant trails and therefore, slow evolution of the algorithm or even, algorithm stagnation). The empirically election of these parameters is a common issue in most optimization algorithms. However, some guidelines can be found in the theoretical basis of this method as well as some range of variation of them [8].

The number of ants and/or iterations in the algorithm, can be selected based on the computational capacity. Actually, in the following examples we have used a relatively low number of ants but a number of iterations large enough to guarantee the convergence of the algorithm to the desired solution. The food is defined as the desired condition i.e, the SLL level, a level of mutual coupling, the wide of band of one antenna, etc.

Finally, the adopted stopping criterium is to complete the selected number of iterations.

3. EXAMPLES

In order to validate the algorithm developed, in this section we will show three examples of design of different electromagnetic structures.

3.1. Thinned Array Design

There are different methods to synthesize a suitable solution using aperiodic arrays. The most common one entails varying the position of the elements symmetrically. However when the number of array elements is large, another option is to use the concept of thinned arrays [18, 19, 20]. In this work we will employ this method, where the positions of the elements will be fixed, but with each element being able to present two states: “on” (when the element is fed) and “off” (when the element is passively terminated in an impedance equal to the source impedance of the fed elements).

According to the structure shown in Fig. 1, where there are 2N elements placed symmetrically along the x-axis, the array factor in azimuth plane (XY plane) can be written as

$$AF(\phi) = 2\sum_{n=1}^{N} I_n cos[\pi \cdot (2n-1) \cdot \cos(\phi)] \quad (4)$$

Where I_n is the excitation amplitude of the n^{th} element. In our case, I_n is 0 if the state of the n^{th} element is “off” and 1 if it is “on”. The distance between elements is 0.5λ and all them have identical current phase.

The array factor for a planar array of $2N$x$2M$ elements (distributed into XY plane) is given by (assuming the same considerations as in the linear array):

$$AF(\theta,\phi) = 4\sum_{n=1}^{N}\sum_{m=1}^{M} I_{nm} cos[\pi \cdot (2n-1) \cdot \sin(\theta)\cos(\phi)] \cdot cos[\pi \cdot (2m-1) \cdot \sin(\theta)\sin(\phi)] \quad (5)$$

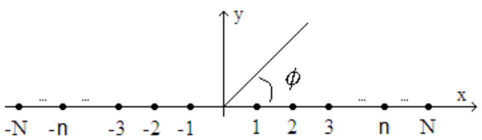

Figure 1. Geometry of a 2N-element symmetric linear array along x-axis

Therefore, we need to find out which array elements should be enabled or disabled ($I_{nm} = 1$ or $I_{nm} = 0$) to get the desired radiation pattern characteristics.

In all the examples we have chosen the parameter values: $\alpha = 5$ and $\beta = 30$.

3.1.1. Linear array with a specific SLL

In this case we search the lowest value of SLL with isotropic elements. The desirability is defined as the absolute value of the normalized SLL (dB’s).

$$\eta_j = |SLL(dB)| \quad (6)$$

Fig. 2 shows the result obtained with 10 ants, 100 iterations and 100 elements. Food was defined as -20dB of SLL. In the same figure the initial case where all the elements were “on” has been plotted. The synthesized array accomplish the design goal.

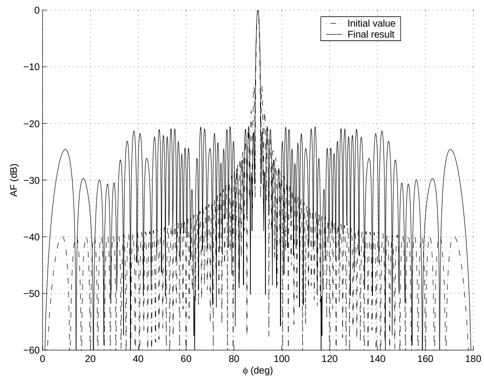

Figure 2. Radiation pattern of a 100-element array obtained by the ant algorithm (dashed line) compared to the initial value (solid line). ($SLL < -20dB$)

Fig. 3 shows the convergence of the algorithm, drawing the best desirability found for each iteration. The algorithm converges in 70 iterations, approximately.

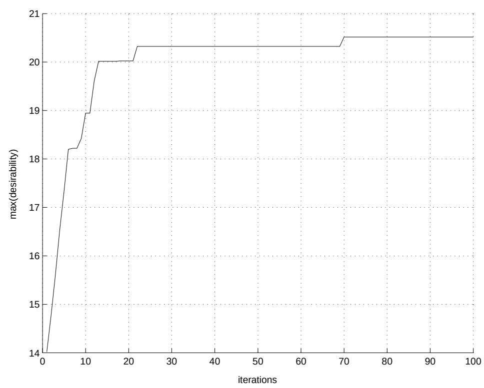

Figure 3. Convergence of the $|SLL|$ value versus the number of iterations

3.1.2. Planar Array

In this section we will deal with the design of a thinned planar array. The SLL level will be checked in the two main planes of the array. In that way, we have used the desirability function given below:

$$\eta_j = min(|SLL_{\phi=0}(dB)|, |SLL_{\phi=90}(dB)|) \quad (7)$$

Fig. 4 shows the result obtained with 10 ants, 100 iterations and 20x10 elements. The food taken to be -24dB of SLL in each plane ($\phi = 0$ and $\phi = 90$). Fig. 5 shows the convergence of the algorithm. The algorithm has a fast convergence (in approximately 40 iterations).

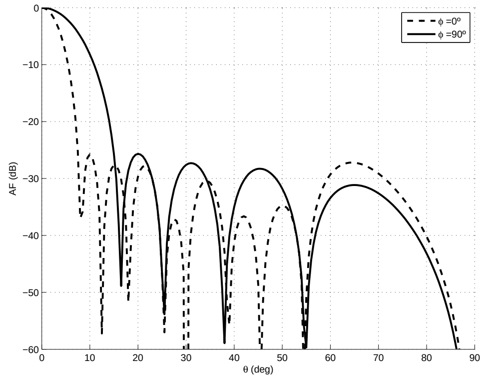

Figure 4. Radiation pattern of 10x20-element planar array in the planes $\phi = 0$ and $\phi = 90$. ($SLL < -24dB$ in both planes)

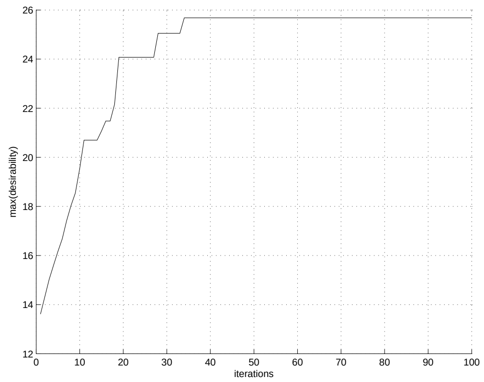

Figure 5. Desirability versus the number of iterations

3.2. Monopolar UWB microstrip antenna

The second example we are going to show in this paper, is the design of a monopolar UWB microstrip antenna (Fig. 6) where the optimization goal is getting s_{11} under $-10dB$ in a band of study. A possible desirability function can be the showed in Eq. 8 where N represents the number of frequency points obtained by the simulation tool (in our case CST Microwave Studio) whose s_{11} values are over $-10dB$.

$$\eta_j = \frac{1}{N} \cdot \sum_{n=1}^{N} (10 - |s_{11}(f_n)|) \qquad (8)$$

In this case, the variables to optimize have been 5: the radii (r and R), the length of the ground plane (L), the wide of the feed line (W) and the distance between the circle and the ground plane (h). The food has been established to 11, in order to be all the time in the *forward way*. The number of ants was 10 and the optimization parameters were: $\alpha = 1$ and $\beta = 30$. The discrete step of variation was $0.5mm$.

The best result obtained, for the used dielectric ($\epsilon_r = 4.5$ with $1.55mm$ of thickness), was with the following parameters: $R = 14.5mm$, $r = 2.5mm$, $h = 0.5mm$, $L = 42mm$ and $W = 57mm$ (Fig. 7 and 8).

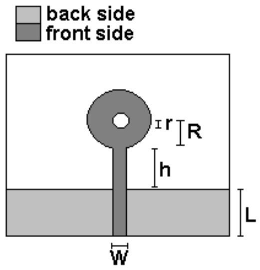

Figure 6. Scheme of a monopolar UWB microstrip antenna

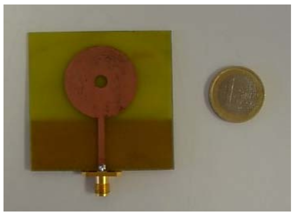

Figure 7. Photography of the monopolar UWB microstrip antenna

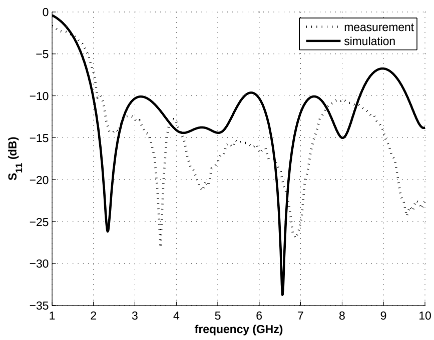

Figure 8. S_{11} parameter after optimization for the monopolar UWB microstrip antenna

3.3. Mutual Coupling Reduction

The starting point is a two element array in a multilayer dielectric substrate, as it is shown in Fig. 9. Both antennas works at $3GHz$. The separation between edges has been chosen to be $40mm$ and the total separation between elements is $75mm$ which is $0.75\lambda_0$. So we have this $40mm$ to place the periodic structure as we force the periodic structure to be placed out of the antennas. Ground plane size is $130mm$.

After that, the periodic structure has to be placed between antennas. As the space between antennas is limited to

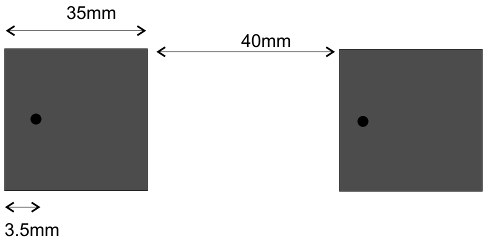

Figure 9. Two element array in a multilayer dielectric substrate for mutual coupling evaluation

$40mm$, only two periods of the periodic structure can be included in E-plane direction. This is a strong limit as in any filtering structure, the larger the number of elements, the better the performance and the filtering. On the other hand, in H-plane direction we have more space and we decide to put four periods of periodic elements. The final design is showed in Fig. 10 and 11.

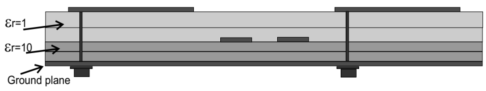

Figure 10. Array of two patches in a multilayer dielectric substrate including a planar periodic structure. Side view.

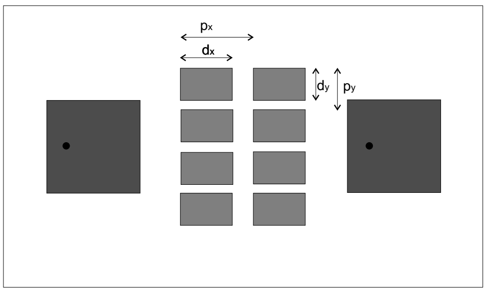

Figure 11. Array of two patches in a multilayer dielectric substrate including a planar periodic structure. Top view.

The initial periodic structure was the one with a size of $d_x = d_y = 15mm$, and $p_x = p_y = 25mm$ that characterize the distance between rectangles. Fig. 12 shows: firstly, the mutual coupling without periodic structure (when the antenna is matched with S_{11} smaller than $-10dB$, the maximum coupling level is $-23dB$); secondly, the mutual coupling for the initial case (with periodic structure), where the maximum mutual coupling in the useful frequency band is $-29dB$, therefore $6dB$ below the case without periodic structure. Moreover, the S_{11} and S_{22} parameters have decreased thus having a better antenna efficiency. Finally, we remark that the mutual coupling without the periodic structure is not very high due to the multilayer structure.

The next step is to try to optimize with an ACO algorithm the design of the periodic structure, i.e. to play with the dimensions of the periodic structure showed in Fig. 11 d_x, d_y, p_x and p_y to further reduce that mutual coupling.

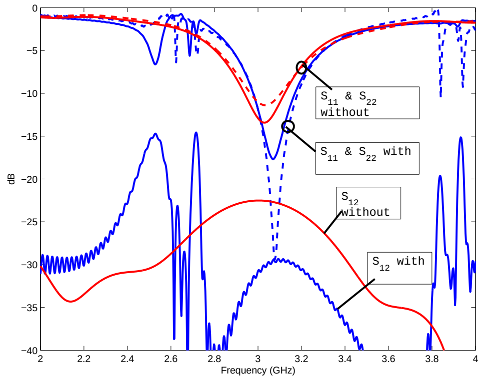

Figure 12. Mutual coupling between antennas in Fig. 9 and input impedance of both antennas with and without periodic structure ($d_x = d_y = 15mm$ and $p_x = p_y = 25mm$) in between.

The only constrain is the space, as the periodic structure has to be placed out of both patch antennas. This optimization is performed using the 8 element periodic structure showed in Fig. 11 for this particular application, i.e. the whole problem will be analyzed.

For this optimization the desirability has been defined as the norm of the module (in dB) of the mutual coupling value at the resonant frequency of the patches. The food has been established to 40, the number of ants was 10 and the optimization parameters were: $\alpha = 5$ and $\beta = 30$. The discrete step of variation was $1mm$.

After several iterations, we find out as best result the one given by $d_x = 13mm$, $d_y = 22mm$, $p_x = 20mm$ and $p_y = 35mm$. We can state that with this method that takes into account the real application of the periodic structure in its design, we find an optimum solution. The mutual coupling has been computed and it is shown in Fig. 13. Here the mutual coupling is under $-35dB$ in all the antenna frequency band. This means a $6dB$ reduction compared to our initial periodic structure and approximately $12dB$ compared to the case without periodic structure. Moreover, the S_{12} parameter shows a clear forbidden band that coincides with the antenna work frequency. Also, the matching of the antennas is excellent.

4. CONCLUSIONS

This work shows how algorithms based on Ant Colony Optimization can be useful in antenna synthesis. Different designs and goals have been defined and results are very promising.

As for the other evolutionary algorithms, the application field is unlimited. Therefore this family of algorithms can join other popular evolutionary optimization techniques (GA, PSO, Simulated Annealing...), as a useful tool for the antenna designer. Though ACO has com-

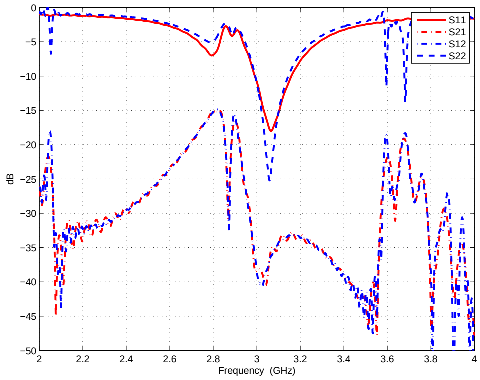

Figure 13. Mutual coupling and matching for the structure described in 11 with $d_x = 7mm$, $d_y = 22mm$ and $p_x = 20mm$, $p_y = 35mm$.

mon features with all of them (because they perform a population-based search with probabilistic transition rules) it presents as advantage its simplicity, robustness, flexibility, intuitive understanding and also an intrinsic local search.

In this work three examples have been used to illustrate the algorithm possibilities. Nevertheless, the application to more complex problems in the electromagnetism area in general is straightforward.

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