Antenna Array Design Methodology Based on a Genetic Algorithm

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Abstract—**In this paper a genetic algorithm is used in the design of a linear antenna array, aiding the designer to find the best antenna for his application. The designer indicates the number of elements of the set, the direction of the main lobe, the side lobe level, and the half-power beamwidth. In this methodology the objective function takes into account the amplitudes and phases of the feeding currents, and the position of each of the elements of the array simultaneously. With this approach, the optimization process covers a larger search space, allowing the designer to achieve a higher number of feasible solutions. Some examples illustrate the potential of the genetic algorithm applied to antenna array designs.**

I. Introduction

The goal of this paper is to provide a methodology for the synthesis of an antenna array based on a genetic algorithm (GA). The GA was chosen as the optimization method because it generally allows the achievement of feasible structures, which frequently does not occur with other optimization methods.

The linear antenna arrays have been widely employed in mobile communication systems. Antenna arrays are flexible, allowing to control the direction of radiation, gain, side lobe level, etc [1]. Thus, it is an interesting technology that can be applied to smart antennas in future third generation (3G) communication systems.

The implemented algorithm yields the several solutions that are near to the optimum response. It is interesting because the designer has the opportunity to choose the most feasible solutions for physical implementation.

Many approaches for antenna array design have been developed. However, these approaches use simplifications that restrict the size of the the search space. In most cases the linear array is symmetric regarding to its centre [2–4]. Thus, only half of the elements of the array need to be actually handled. Moreover, some algorithms work with constant distances and phase differences between the elements of the array [3–6].

The methodology proposed in this paper is flexible and innovates by allowing the synthesis of a non-symmetric linear antenna array. Additionally, all of the antenna parameters can be optimized. This allows the designer to find optimized structures through the variation of the number of elements of the array, the amplitudes and phases of the feeding currents, and positions of the elements. These modifications increase the number of possible design solutions.

II. Linear Array Antenna

The radiation pattern of the antenna array is determined by the types of elements used and their spatial positions, and by the amplitudes and phases of the feeding currents of the elements. The array factor was used to simplify the computation, where each array element is considered as an isotropic punctual source.

The array factor (AF) is given by the following expression [7]:

$$AF(\theta,\phi) = \sum_{n=0}^{N-1} A_n e^{jn(\beta d \cos\phi \sin\theta + \alpha)} \tag{1}$$

It is assumed that the array is linear and has the reference axes in the first element. The parameters of (1) are

N = number of elements in the array;
β = phase propagation factor;
θ = elevation angle;
ϕ = azimuthal angle;
A_n = amplitude weight of element n;
d = spacing between elements;
α = relative phase between adjacent elements.

It can be noticed in (1) that the elements of the array are uniformly spaced and the phase difference between them is constant. It is not desirable because it decreases the degree of freedom of the antenna design. To solve this problem, expression (1) can be generalized in such a way that all parameters can be handled. The resulting expression is the following:

$$AF(\theta,\phi) = \sum_{n=0}^{N-1} A_n e^{j(\beta x_n \cos\phi \sin\theta + \alpha_n)} \tag{2}$$

for

$$n = 0 \Longrightarrow x_n = x_0 = 0$$

$$n \neq 0 \Longrightarrow x_n = \sum_{m=1}^{n} d_m$$

where

x_n = position of the element n;
α_n = phase weight of element n.

Fig.1 shows the position of the elements in the axis-x. The spacings and the amplitudes and phases of the feeding currents of each element can be set to any value.

The case in which a wave is incident on the array in the x–y plane so that $\theta \approx \pi/2$ in (2) is considered in this paper. This is a reasonable approximation for smart antenna applications, especially in cellular and Personal Communications Systems [8].

The parameters of an antenna array considered in this paper are the main lobe direction, the side lobe level, and the half-power beamwidth. The side lobe level (SLL) is defined as the ratio between the peak value of the larger side lobe and the peak value of the main lobe. The width of the main beam is quantified through half-power beamwidth (HP), which is the angular separation of the points where the main beam of the power pattern equals one-half the maximum value [7].

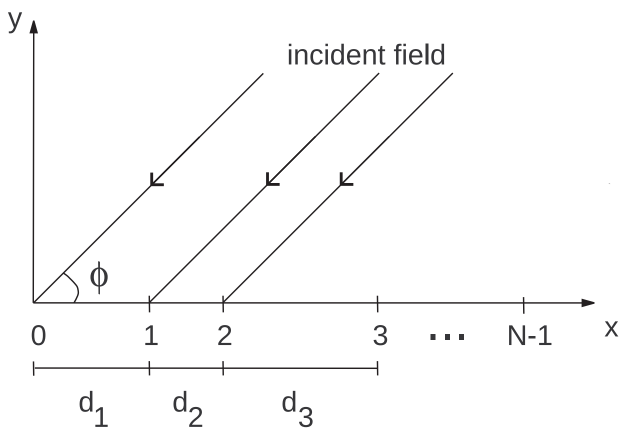

Fig. 1. A diagram of a nonuniformly spaced linear array.

III. THE GENETIC ALGORITHM

The genetic algorithm is inspired on the evolution mechanism and uses the concepts of the origin of the species and of natural genetics, proposed by Darwin and Mendel, respectively.

GA optimizers are robust, stochastic search methods modeled on the principles and concepts of natural selection and evolution [5].

GAs were introduced by John Holland in the seventies as a special technique for function optimization [9]. They differ from most optimization methods and they have the following characteristics [10]:

1. They work with a coding of the parameters set, not the parameters themselves.
2. They search for many points instead of a single point.
3. They don't use derivatives or other auxiliary knowledge.
4. They use probabilistic transition rules, not deterministic rules.

Since the GA has a strong inspiration on the theory of the evolution of the species and on the natural genetics, many terms from biology are used. For example, it is known that any individual is composed by a set of chromosomes. Then, an analogy between individual and chromosome is done in the GA.

The flowchart in Fig.2 shows the cycle of the GA. Before the GA execution, the parameters (genes) to be controlled by the algorithm must be defined. Additionally, the specific fitness function must also be described. The aim of the fitness function is to determine a fitness value for each individual of the population.

Each individual represented by a chromosome is built by binary codification of the real parameters of the problem. The algorithm starts with the random generation of the individuals of the population, which are possible solutions for the problem.

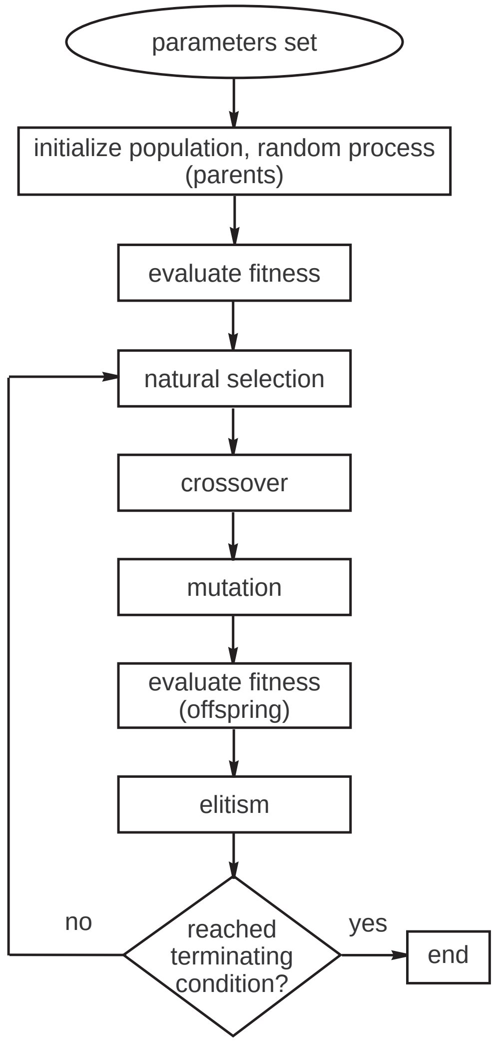

Fig. 2. The genetic algorithm cycle.

All of the generated individuals (parents) are evaluated by the fitness function. The nature selection, the crossover, the mutation, and the elitism are genetic operators used to manipulate the individuals. They are used to search the most adapted individuals which are better solutions for the proposed problem.

The idea of natural selection is similar to that presented by Darwin in his theory of the origin of species. The most adapted individuals of the generation have higher probabilities to survive and therefore have higher probabilities to participate in the process that generates the next population. After each individual is evaluated, a binary tournament is carried out. This tournament is performed in order to choose randomly the mates that will participate in the crossover process [5].

Two individuals are randomly selected from the population to form a pair of mates. The one that has the best fitness value is the first element of the couple. The second one comes from a new draw of two individuals. The one with better fitness remains. A couple is composed by different individuals but an individual can participate of several crossovers.

Each previously selected couple crosses, with a given probability, generating then two new individuals of the next generation. The crossover happens with the random change of genetic material between the elements of the couple (parents). The type of crossover implemented exchange the bits between two cut sites.

The mutation is of fundamental importance because it allows the sweeping of the entire search space of solutions. Depending on the initial population, without using the mutation operator, an acceptable solution may not be found. The mutation helps to avoid a local minimum and guarantees the genetic diversity of the population. The mutation mechanism consists of changing (1 to 0 or 0 to 1) one or more bits of the chromosome with a given probability [6].

In order to preserve the best individuals of the population, i.e. the best solutions, the elitism mechanism is implemented. This mechanism ensures that the most adapted individuals will be in the new population. In the case in which the best individual of the old population is not better than the worst of the new population, elitism does not occur.

The population evolves until the end of a pre-defined number of iterations (generations) or when a stopping criterion is reached. In the stopping criterion, the performance of the population is analyzed in order to evaluate if the desired goals were achieved. The stopping criterion that can be used is: if a given percentile of individuals approximately meets the design goals, the optimization process ends and these individuals are taken as solutions of the problem [10].

Fig.3 illustrates the result of the GA applied to an example. It shows the fitness values of the individuals of the population. In this example ninety individuals constitute the population and the maximum fitness value is 30. It can be seen that there are some individuals presenting fitness values very close to the maximum. The others are in an intermediate range and there are some with low fitness values. The achievement of more than one good solution demonstrates the versatility of the GA.

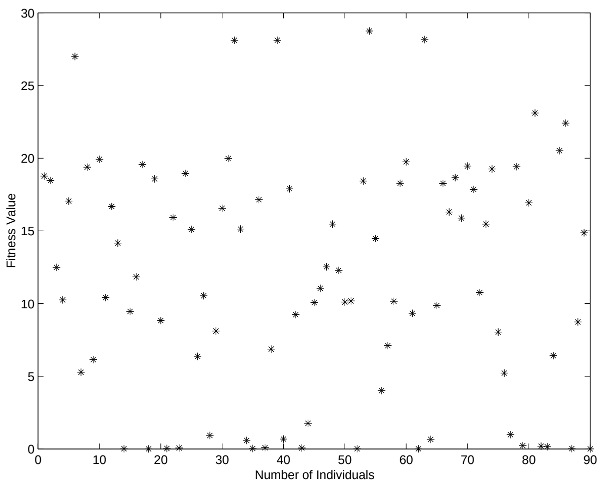

Fig. 3. Result of the genetic algorithm.

IV. Fitness Function Definition

The fitness function is an important factor for the success of the optimization based on a genetic algorithm. In this paper, we use a special function to achieve a desired direction (ϕ_d), a desired side lobe level (SLL_d), and a desired half-power beamwidth (HP_d).

The fitness function used in the algorithm is composed by a sum of three Gaussian functions, each one representing one of the parameters mentioned above.

$$\begin{aligned} Apt &= K_1 e^{\frac{-(\phi_0-\phi_d)^2}{H_1}} + \\ &+ K_2 e^{\frac{-(SLL-SLL_d)^2}{H_2}} + \\ &+ K_3 e^{\frac{-(HP-HP_d)^2}{H_3}} \end{aligned} \tag{3}$$

where

ϕ_0 = main lobe direction;
SLL = side lobe level;
HP = half-power beamwidth.

The values of K_i and H_i, $i = 1, 2, 3$, vary accordingly with the objective of the design. K_i represents the weight of each term of the fitness function.

The proposal of the Gaussian behavior has the objective of providing an improved control of the sensitivity of the fitness function regarding to the optimization parameters, as well as, to avoid the predominance of one of the search parameters over the others by equally distributing the contributions of each parameter.

V. Results

To demonstrate the potential of the proposed methodology, the design of a linear antenna array with five elements equally spaced by 0.5λ was carried out. As an example, an array with main lobe direction $\phi_d = 90°$, side lobe level $SLL_d = -40dB$, and half-power beamwidth $HP_d = 30.5°$ was designed. These values were chosen to show the efficiency of the algorithm through the comparison with an antenna array presenting a binomial current amplitude distribution ($1 : 4 : 6 : 4 : 1$) and the current phases of the feeding currents of the elements are null.

The results were obtained by using a linear array with five isotropic punctual sources. Uniform distances of 0.5λ between array elements were considered in the design. The optimization parameters were the amplitudes and phases of feeding currents of the elements. The amplitudes were distributed linearly in eight different levels along the range 0 to 7 and codified using 3 bits. When the amplitude is zero the corresponding element can be taken out of the array. The phases were coded using 12 bits along the range 0 to 360°.

In this paper, the weight of terms of the fitness function were $K_1 = K_2 = K_3 = 10$, $H_1 = 1000$, $H_2 = 200$ and $H_3 = 150$.

The GA was processed for a population of 80 individuals. This amount of individuals obeys the heuristic that states that the number of bits in a chromosome must equal the number of individuals (chromosomes). Table I presents the values of the main lobe direction, the side lobe level, and the half-power beamwidth obtained for the four best results. Figs.4 and 5 show,

TABLE I

VALUES OBTAINED FOR THE ARRAYS OF FIVE ELEMENTS.

Array	ϕ (degrees)	SLL (dB)	HP (degrees)
1	90.0	-40.0	30.5
2	90.6	-40.0	30.5
3	89.4	-40.0	30.5
4	90.0	-40.0	30.0

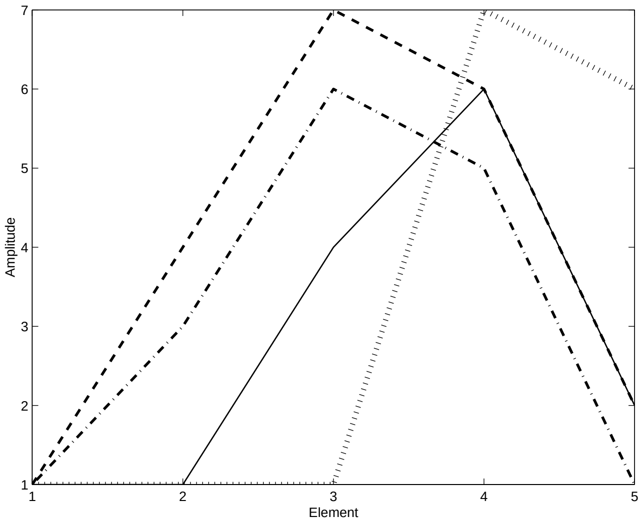

Fig. 4. Amplitude of the array elements scaled from 0 to 7.

respectively, the feeding amplitudes and phases of these four solutions.

Fig.6 illustrates the radiation pattern presented in [7], as well as the radiation pattern of the best array. The distribution of the amplitudes of the feedings currents are given by $1:1:4:6:2$ and the phases are $31.9°:0°:359.1°:9.8°:15.6°$. This result shows that it is possible to obtain radiation patterns by applying different current excitations in the elements.

In Fig.5 it can be noticed that one of the results presents elements with almost constant phases. It makes the physical implementation of the antenna array easy, because the number of circuits for array operation is reduced.

Based on Table I it can be seen that the results are close to the design goals. Figs.4 and 5 and Table I also show the potentiality of the GA in the design of an antenna array. By generating several arrays that meet the specifications, the most suitable one (regarding technology and application) can be chosen.

In a second example, variations of the distances between elements (0.25λ to 0.625λ) were allowed (4 coding bits). The aim is to show that it is also possible to achieve results with arrays presenting low dimensions.

Table II shows the spacings between the elements for four arrays obtained along the optimization process that meet the design goals. From this table it can be noticed that the final dimension of the arrays can be reduced by applying the methodology proposed in this paper.

Fig.7 illustrates the expected radiation pattern and the one of the array with the lower dimension achieved. The current amplitude distribution in the five elements is $2:0:4:2:4$ and the

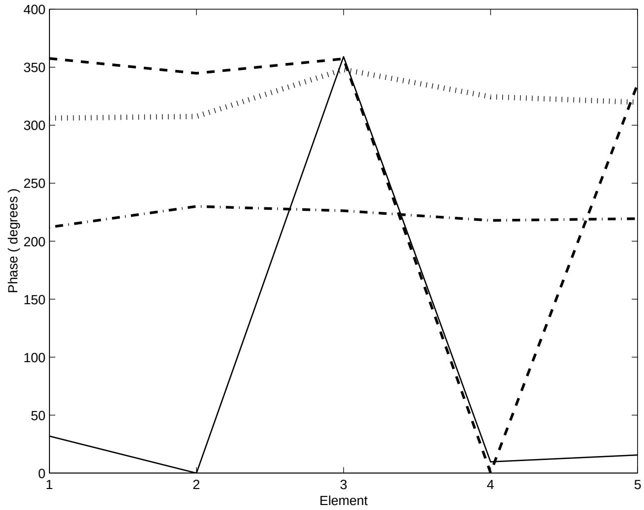

Fig. 5. Phase of the array elements scaled from 0 to $360°$.

phase distribution is $276.1°:90.8°:279.6°:280.4°:273.4°$. For this antenna array the obtained main lobe direction was $89.6°$, the side lobe level was $-39.7dB$, and the half-power beamwidth was $33.5°$. These results are within the error range of 10%.

VI. CONCLUSION

By using a genetic algorithm as an optimization method, a methodology applied to the design of antenna arrays was developed. In this methodology, it is possible to simultaneously define the main lobe direction, the side lobe level, and the half-power beamwidth of the antenna array. A new strategy to formulate the fitness function was also presented. This scheme showed efficiency in obtaining the desired array behavior, avoiding the

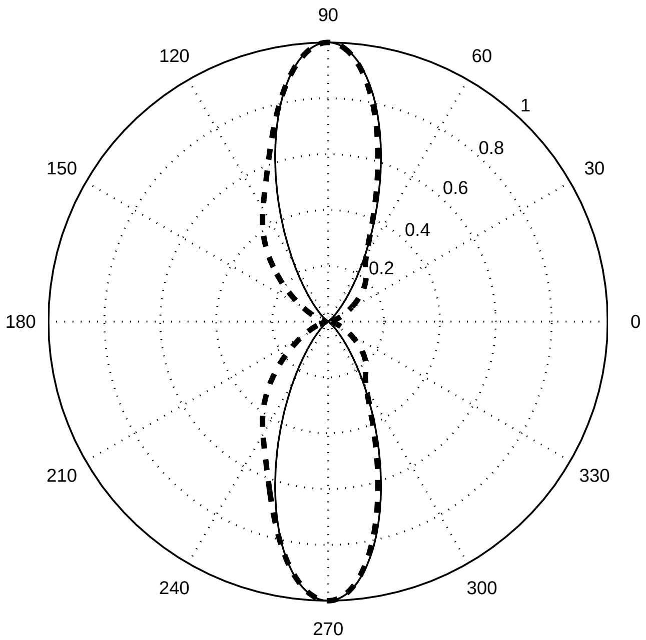

Fig. 6. Field linear normalized radiation pattern of the best array obtained (- - -) and the one (—) presented in [7]. The linear array is equally spaced.

TABLE II

SPACINGS OBTAINED FOR THE ARRAYS WITH FIVE ELEMENTS.

Array	d_1 (λ)	d_2 (λ)	d_3 (λ)	d_4 (λ)
1	0.300	0.375	0.325	0.325
2	0.550	0.575	0.475	0.425
3	0.325	0.375	0.300	0.350
4	0.250	0.375	0.375	0.275

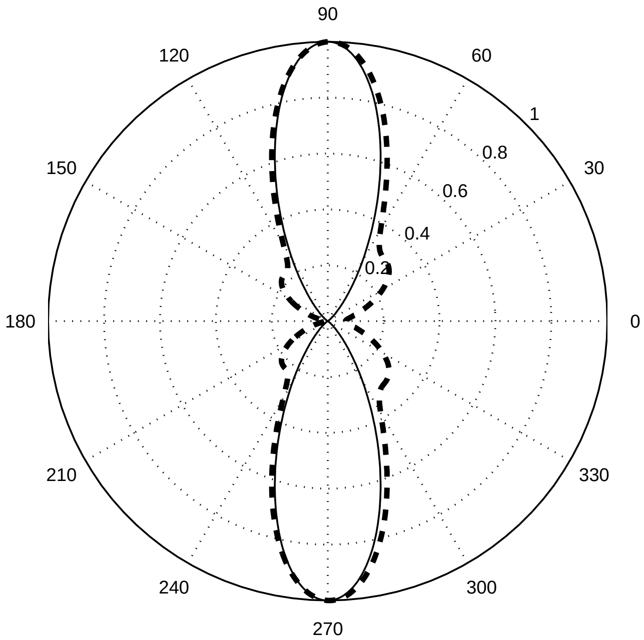

Fig. 7. Field linear normalized radiation pattern of the best array obtained (- - -) and the one (—) presented in [7]. The linear array is nonuniformly spaced.

predominance of one characteristic over the others. Examples considering linear antenna arrays with five isotropic elements were shown. The results obtained were compared with the ones in the bibliography. The methodology presented in this paper allows the attainment of a multitude of antenna arrays that meet the design goals. This is an interesting characteristic because the designer will be able to choose the most suitable one with respect to physical implementation and costs.

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