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SYNTHESIS OF THINNED LINEAR ANTENNA ARRAYS WITH FIXED SIDELOBE LEVEL USING REAL-CODED GENETIC ALGORITHM

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Abstract—In this paper, we propose an optimization method based on real-coded genetic algorithm (GA) with elitist strategy for thinning a large linear array of uniformly excited isotropic antennas to yield the maximum relative sidelobe level (SLL) equal to or below a fixed level. The percentage of thinning is always kept equal to or above a fixed value. Two examples have been proposed and solved with different objectives and with different value of percentage of thinning that will produce nearly the same sidelobe level. Directivities of the thinned arrays are found out and simulation results of different problems are also compared with published results to illustrate the effectiveness of the proposed method.

1. INTRODUCTION

Uniformly excited and equally spaced linear antenna arrays [1] have high directivity but they usually suffer from high sidelobe level. To reduce the sidelobe level, the array is made aperiodic by altering the positions of the antenna elements nonuniformly with all excitation amplitudes being uniform. Another possibility is to use an equally spaced array with tapered amplitude distribution [1]. However, uniform excitation is desired to minimize the complexity in designing a feed network.

It is not possible to design a thinned array using analytical methods as the synthesis problem is complex. Therefore, global optimization tools are a good option to solve these problems. Among the different global optimization methods such as genetic algorithms (GA) [2, 3], particle swarm optimization (PSO) [4], simulated annealing (SA) [5] etc. have already been utilized in array antenna synthesis for various applications.

There are many published articles [6–8] dealing with the synthesis of thinned array. Element behavior in a thinned array is described in [9]. Some of the other applications of soft computing tools are discussed in [10, 11].

Real-coded GA is nicely described in the book [12] and the applications of genetic algorithms in the field of electromagnetics are discussed in [13, 14].

Lee et al. [15] described optimization of unequally spaced antenna arrays using particle swarm algorithm. Applications of real-coded genetic algorithms for the design of reconfigurable array antennas are discussed in [16, 17].

Some of the latest soft computing tools such as clonal selection algorithm [18] and bees algorithm [19] have been successfully used in array antenna synthesis for different applications.

In this paper, we have presented two examples one without the end element of the array being switched off and another with the end element being intentionally switched off. The objective is to shorten the length of the thinned array by removing the switched off end elements from either side of the array when there is no coupling between the elements. This is in addition to fulfillment of other requirements of designing the thinned array.

2. THINNED ARRAY SYNTHESIS

Thinning an array means turning off some elements in a uniformly spaced or periodic array to generate a pattern with low sidelobe level. In our proposed method, the positions of the elements are fixed and all the elements have two states either "on" or "off", depending on whether the element is connected to the feed network or not. In the "off" state, the element is passively terminated to a matched load. If there is no coupling between the elements, it is equivalent to removing them from the array.

Thinning an array [7] to produce low sidelobes is much simpler than unequally spacing the elements for generating pattern with low sidelobe level. There are infinite numbers of possibilities for placement of the elements nonuniformly. However, thinning has $2P$ possible combinations, where P is the number of array elements. If the array is symmetric, then the number of possibilities is substantially smaller.

We consider a linear array of $2N$ isotropic antennas, which are assumed uncoupled, symmetrically and equally spaced a distance d apart along the x-axis with its center at the origin. It is shown in Fig. 1.

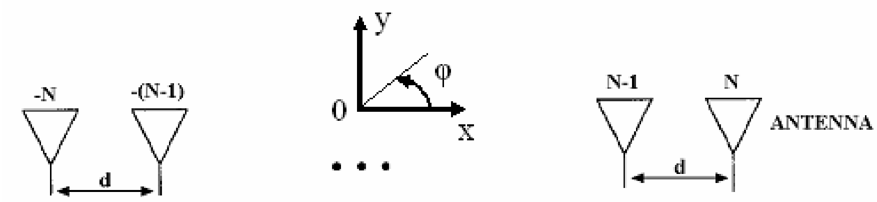

Figure 1. Geometry of a $2N$-element symmetric linear array along the x-axis.

The free space far-field pattern $F(\phi)$ in azimuth plane (x-y plane) with symmetric amplitude distributions [1] is given by eqn. (1):

$$F(\phi) = \sum_{n=1}^{N} 2I_n \cos[(n - 0.5)kd \cos\phi] \tag{1}$$

Here the elements are numbered from the array center and array center is at the origin.

Where $n =$ element number, $d =$ interelement spacing $=0.5\,\lambda$, $k = 2\pi/\lambda$, being wave number, λ = wavelength, ϕ being azimuth angle of the far-field point measured from x-axis, I_n = excitation amplitude of the n-th element ($I_n = I_{-n}$). In our case, I_n is 1 if the n-th element is turned "on" and 0 if it is "off". All the elements have same excitation phase.

Normalized power pattern, $P(\phi)$ in dB can be expressed as follows:

$$P(\phi) = 10 \log 10 \left[\frac{|F(\phi)}{|F(\phi)|_{\max}} \right]^2 = 20 \log 10 \left[\frac{|F(\phi)}{|F(\phi)|_{\max}} \right] \tag{2}$$

The fitness function to be minimized with real-coded GA for optimal synthesis of thinned array is given in eqn. (3).

$$Fitness = c_1(SLL_o - SLL_d)^2 H(X) + c_2(TH_o - TH_d)^2 H(Y) \tag{3}$$

Where SLL_o, SLL_d are obtained and desired value of sidelobe level in dB, TH_o, TH_d are obtained and desired value of percentage of thinning, c_1, c_2 are weighting coefficients to control the relative importance given to each term of eqn. (3).

$H(X)$ and $H(Y)$ are Heaviside step functions defined as follows:

$$X = (SLL_o - SLL_d), \quad Y = (TH_o - TH_d) \tag{4}$$

$$[H(X), H(Y)] = \begin{cases} [1, 0], & \text{if} \quad X \geq 0,\ Y > 0 \\ [0, 1], & \text{if} \quad X < 0,\ Y \leq 0 \end{cases} \tag{5}$$

3. REAL-CODED GA OPTIMIZATION OVERVIEW

Genetic Algorithm [12] is an iterative stochastic optimizer that works on the concept of survival of the fittest, motivated by Darwin, and uses methods based on the principle of natural genetics and natural selection to construct search and optimization procedures that best satisfies a predefined goal.

Real-coded GA [12] uses floating-point number representation for the real variables and thus is free from binary encoding and decoding. In floating-point representation, each chromosome or individual vector is coded as a vector of floating-point numbers of the same length as the solution vector. The precision of such an approach depends on the underlying machine. It takes less memory space than binary GA.

The flow chart diagram of real-coded GA is shown in Fig. 2 below.

A population is a collection of individuals or solutions and an individual is a group of variables. The three genetic operators [12] are selection, crossover and mutation. They are the cores of the algorithm. Elitist strategy has been applied in real-coded GA. It is summarized as follows:

Step 1: Randomly generate an initial population of P individuals within the variable constraint range.

Step 2: Evaluate the fitness of the individuals from the fitness function.

Step 3: Select the superior individuals using nonlinear ranking [12] and place them in the mating pool. Numbers of individuals in the mating pool are same as P in order to accommodate more copies of superior individuals in the new population. Highly fit individuals get more copies in the mating pool, whereas the less fit ones get fewer copies.

Step 4: Individuals so called parents placed in the mating pool are now allowed to mate followed by mutate using heuristic crossover and uniform mutation [12] respectively. In the crossover process,

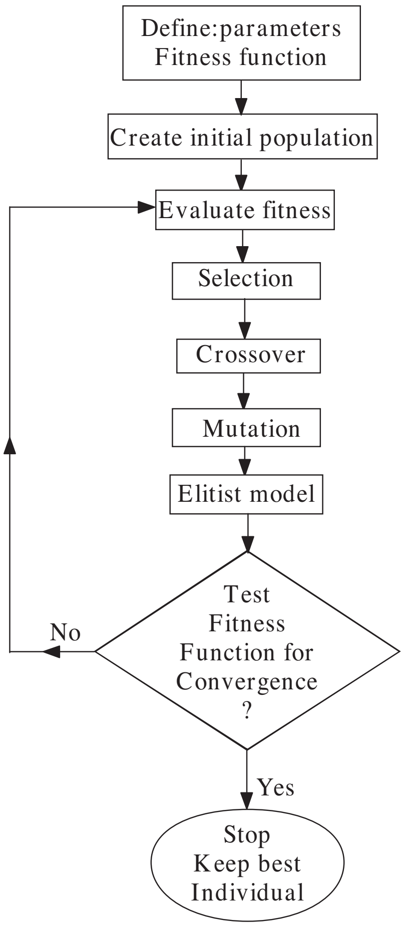

Figure 2. Flow chart diagram of real-coded GA.

two parents mate each other to produce two children. Subsequent mutations of the parents add diversity to the population and explore new areas of parameter search space. Select C pairs of parents at random from the mating pool to participate in crossover to produce C pairs of offspring and replace the chosen C pairs of parents from the mating pool with these new C pairs of crossover offspring.

Select M number of parents at random from the mating pool to take part in mutation to produce M number of offspring and replace the chosen M number of parents from the mating pool with these new M number of mutation offspring. Mutation only changes one variable of a parent.

Step 5: The postprocessor is the elitist model. The worst individual in the newly generated population is replaced by the best individual in the old population. It is adopted to ensure the algorithm's convergence. This step has been introduced to prevent loosing the best-found individuals by chance because of crossover and mutation. It will always preserve the best individual from one generation to the next.

Step 6: Repeat steps 2–5 until a stopping criterion, such as a sufficiently good solution being discovered or a maximum number of generations being completed, is satisfied. The best scoring individual in the population is taken as the final answer.

4. RESULTS

We consider a linear array of 100 isotropic antennas symmetrically spaced 0.5λ apart along x-axis with its center at the origin in order to generate a broadside symmetric pattern in azimuth plane (x-y plane) with desired sidelobe level of -20 dB or below and percentage of thinning equal to 22 or above. The excitation amplitude distribution is symmetric with respect to the center of the array.

Because of symmetry, only 50 amplitudes are to be optimized. In this paper, two examples have been presented one without the end element being switched off and another with the end element being intentionally switched off. This part is done to reduce the length of the thinned array when there is no coupling between the elements. The proposed fitness function is different from [6, 7].

For the two cases, GA is run independently twice with fixed number of generations, each time with different set of initial population of size 200 by setting the seed of random number. Selection operator used in GA is nonlinear ranking with probability of 0.15 for selecting the best individual. Number of retries in heuristic crossover is taken to be three and GA is run for 300 generations for both the cases.

Crossover and mutation operators are called 100 times every generation in order to ensure that only 100 pairs of parents take part in crossover and 100 numbers of parents take part in mutation in stead of all. This will reduce the overall computational time in optimization considerably.

4.1. Case 1

In this case, no restriction is imposed on the optimization algorithm to switch on or off the end element of the array. Fitness function is minimized using real-coded GA as usual.

The sidelobe level obtained is -20.56 dB and thinning is 22%. The percentage of thinning obtained is more than that of [6], where it is 20% and that too without sacrificing sidelobe level. Fig. 3 shows the normalized power pattern in dB for case 1. Table 1 shows the element numbers which are switched off. Different results are displayed in Table 2.

Table 1. Switched off element numbers for both the cases.

	Switched off element numbers
Case 1	±28, ±33, ±34, ±38, ±40, ±41, ±42, ±43, ±45, ±48, ±49
Case 2	±29, ±31, ±35, ±36, ±39, ±40, ±42, ±43, ±44, ±45, ±48, ±50

Table 2. Comparative results.

Design parameters	**Our proposed design**		**Óscar Quevedo-Teruel *et al*. [6]**
	Case 1	**Case 2**	
Percentage of thinning	22.00	24.00	20.00
Sidelobe level(dB)	-20.56	-20.53	-20.50
Directivities(dB)	18.92	18.80	19.03

4.2. Case 2

In this case, the end element of the array is forcefully switched off in order to reduce the length of the thinned array. In an array environment if there is no coupling between the elements, switching off an element is equivalent to removing it from the array. In this respect, our proposed method is different from [6].

The sidelobe level obtained is -20.53 dB and thinning is 24%.

Fig. 4 shows the normalized power pattern in dB for case 2. Table 1 shows the element numbers which are switched off.

Details of comparative studies such as percentage of thinning, sidelobe level and directivities of our proposed thinned array are carried out with respect to the article [6] and shown in Table 2.

From the comparison as shown in Table 2, it has been found that our optimally designed thinned arrays are better in terms of percentage of thinning than [6] without sacrificing the sidelobe level but with little sacrifice in directivities. Additionally while considering the size of the

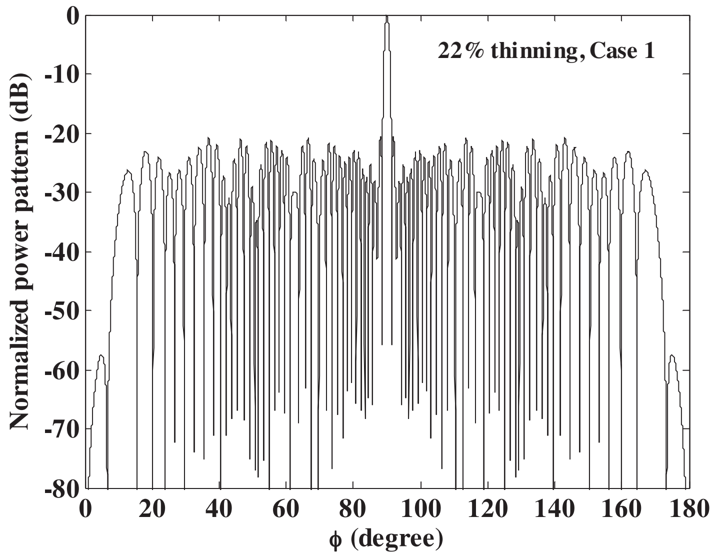

Figure 3. Normalized power pattern in dB for 22% thinned array (Case 1).

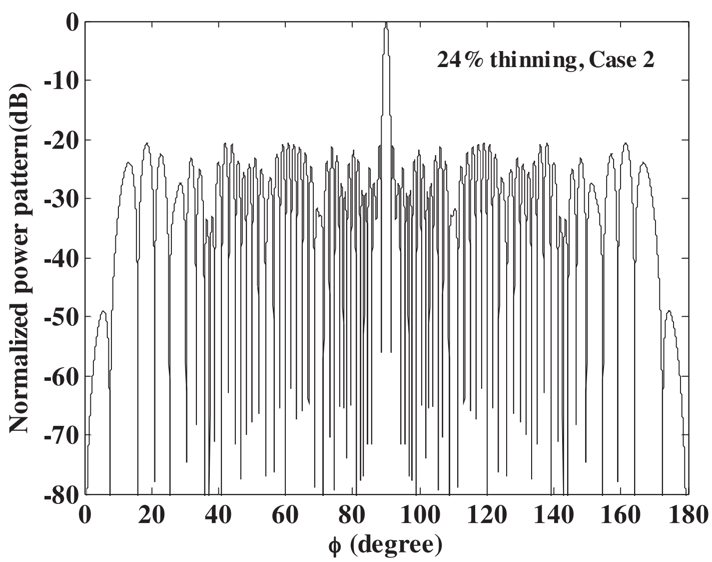

Figure 4. Normalized power pattern in dB for 24% thinned array (Case 2).

array, our proposed case 2 design takes less space than [6] as its end element on either side of the array is switched off.

5. CONCLUSION

The paper presents a new technique for designing a thinned linear antenna array with fixed sidelobe level and fixed percentage of thinning using global optimization tool such as real-coded genetic algorithm with elitist strategy. Two examples have been presented in the paper with different objectives. One of the objectives is to reduce the length of the thinned array by removing the switched off end element from either side of the array when there is no coupling between the elements. Results clearly show a very good agreement between the desired and synthesized specifications for both the cases.

Results for a thinned linear isotropic antenna array have illustrated the performance of this proposed technique. This method is very simple and can be used in practice to synthesize a thinned planar array.

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