Dr. R. Ramana Reddy, S.M. Vali, P.Divakara Varma / International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622 www.ijera.com
Vol. 3, Issue 4, Jul-Aug 2013, pp.1312-1317

Reduction of Side Lobe Levels of Sum Patterns from Discrete Arrays Using Genetic Algorithm

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ABSTRACT

Antennas are vital elements in any wireless communication systems. Radiation pattern is an important characteristic of an antenna. Radiation pattern of a single antenna element is fixed. Required radiation patterns can be generated from array of antennas.
Different pattern synthesis techniques are reported in the literature. Generated patterns from selected pattern synthesis techniques can further be optimized using optimization techniques like genetic algorithms. Genetic Algorithm(GA) is a popular optimization technique for better solutions. A typical genetic algorithm requires genetic representation of the solution domain, fitness function to evaluate the solution domain.
Once the genetic representation and the fitness function are defined, a GA proceeds to initialize a population of solutions and then to improve it through repetitive application of the mutation, crossover, inversion and selection operators. Sum patterns are generated using Fourier synthesis technique. The task of reducing the side lobe levels of generated sum patterns using optimization technique is considered in this work.

***Keywords* -** Antenna, Genetic Algorithm, optimization, Radiation patterns, side lobe level,

I. INTRODUCTION

In Electromagnetics research is concentrated on finding a solution to an integral or differential equation with boundary conditions. One problem has one solution. Finding such a solution has proved quite difficult. Rather than finding a single solution, optimization [1] implies finding many solutions then selecting the best one. Optimization is an inherently slow, difficult procedure, but it is extremely useful when well done

II. OPTIMIZING THE FUNCTION OF ONE VARIABLE

Most practical optimization problems have many variables. Many of the multidimensional optimization routines rely on some version of the one-dimensional optimization algorithms.
Optimization implies finding either the minimum or maximum of an objective function, that is to be optimized. A variable is passed to the objective function and a value returned. The goal of optimization is to find the combination of variables that causes the objective function to return the highest or lowest possible value.
For a six element equally spaced array when the signal is incident at an angle φ, and end elements have same variable amplitude, only one minima can be obtained by optimizing the objective function as given in the equation (1)

$$(AF)_1(a) = 1/6 \ |a + e^{j\Psi} + e^{j2\Psi} + ae^{j3\Psi}| \quad (1)$$

where $\Psi = k\,du$,
$k = 2\pi/\lambda$
λ = wavelength,
$u = \cos\varphi$

for the same array [2] with uniform amplitude but conjugate phases at the end elements the objective function is given in equation(2) is more complex and has two minimas, a different technique is needed to find successful minima.

$$AF_2(\delta) = 1/6 \ e^{j\delta} + e^{j\Psi} + e^{j2\Psi} + e^{-j\delta}e^{j3\Psi} \quad (2)$$

Usually, arrays have many elements, hence many variables need to be adjusted in order to optimize some aspect of the antenna pattern. To demonstrate the complexity of dealing with multiple dimensions, the objective functions in equations (1) and (2) are extended to two variables and three angle evaluations of the array factor [3].

$$AF_3(a_1,a_2) = \frac{1}{6}\sum_{m=1}^{3}| a2 + a1e^{j\Psi m} + e^{2j\Psi m} + e^{3j\Psi m} + e^{4j\Psi m} + e^{5j\Psi m} | \quad (3)$$

$$AF_4(\delta 1, \delta 2) = \frac{1}{6}\sum_{m=1}^{3}| e^{j\delta 2} + e^{j\delta 1}e^{j\psi m} + e^{2j\Psi m} + e^{3j\Psi m} + e^{j\delta 1}e^{4j\psi m} + e^{j\delta 2}e^{5j\Psi m} | \quad (4)$$

III. GENETIC ALGORITHM

A genetic algorithm [4] is a search technique used in computing to find exact or approximate solutions to optimization and search problems. Genetic algorithms are a particular class of evolutionary algorithms based on mechanics of natural selection and natural genetics that use techniques inspired by evolutionary biology such as inheritance, mutation, selection, and crossover.

Differences between Genetic Algorithms and traditional methods

Genetic algorithms are different from normal optimization and search procedures, like direct and indirect calculus-based methods, enumerative schemes, random search algorithms etc, in four ways:

- It works on coding of the parameter set, not the parameters themselves.
- It searches from a population of points, not a single point.
- It uses objective function information, not the derivative or other auxiliary knowledge.
- It uses probabilistic transition rules, not deterministic rules.

In traditional optimization methods, we move gingerly from a single point in the decision space to the next using some transitional rule to determine the next point. The point-to-point method is dangerous because it is perfect prescription for locating false peak in multi-modal search spaces. By contrast, genetic algorithm works from a rich database of points simultaneously climbing many peaks in parallel, thus probability of finding a false peak is reduced over that go point-to-point.

Many search techniques [5] require much auxiliary information in order to work properly. In contrast, genetic algorithm requires only objective function values associated with individual string. Unlike other methods, genetic algorithms use random choice as a tool to guide a search toward regions of the search space with likely improvement.

Genetic algorithm are implemented as a computer simulation in which a population of abstract representations called chromosomes of candidate solutions to an optimization problem evolves toward better solutions. The evolution starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population based on their fitness, and modified to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population. If the algorithm has terminated due to a maximum number of generations, a satisfactory solution may or may not have been reached. A typical genetic algorithm requires two things to be defined:

- a genetic representation of the solution domain.
- a fitness function to evaluate the solution domain.

A standard representation of the solution is as an array of bits. Arrays of other types and structures can be used in essentially the same way.

The fitness function is defined over the genetic representation and measures the quality of the represented solution. The fitness function is always problem dependent. Once we have the genetic representation and the fitness function defined, GA proceeds to initialize a population of solutions randomly, and then improve it through repetitive application of mutation, crossover and selection operators.

IV. IMPLEMENTATION OF GENETIC ALGORITHM

Input to an objective function is a chromosome. The output of the objective function is known as the cost when minimizing. Each chromosome consists of genes or individual variables. The genes take on certain alleles much as the variable has certain values. A group of chromosomes is known as a population.

$$population = \begin{bmatrix} chrome1 \\ chrome2 \\ . \\ . \\ . \\ chromeN \end{bmatrix} = \begin{bmatrix} \begin{pmatrix} g_{11}\, g_{12} \cdots g_{1m} \\ g_{21}\, g_{22} \cdots g_{2m} \\ . \quad . \\ . \quad . \\ g_{n1} g_{n2} \cdots g_{nm} \end{pmatrix} \end{bmatrix} = \begin{bmatrix} red & 1 & ..... & 19.132 \\ blue & 5 & ..... & -15.367 \\ . & . & & . \\ . & & & \\ . & & & \\ green & 2 & ..... & 0.521 \end{bmatrix}$$

Chromosomes genes Values or alleles

(5)

Each chromosome is the input to an objective function f. The cost associated with each chromosome is calculated by the objective function one at a time or in parallel.

$$f\begin{bmatrix} \begin{pmatrix} chrome\ 1 \\ chrome\ 2 \\ . \\ . \quad\quad . \\ chrome\ n \end{pmatrix} \end{bmatrix} = \begin{bmatrix} \cos t\,1 \\ \cos t\,2 \\ . \\ . \\ \cos t\,N \end{bmatrix} \tag{6}$$

It is the cost that determines the fitness of an individual in the population. A low cost implies a high fitness.

The steps to be followed in implementing genetic algorithm [6] are shown below as a flowchart in figure 1.

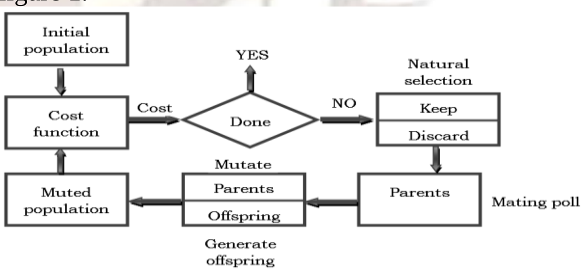


Fig. 1 . Flowchart for implementing Genetic Algorithm.

The generational process is repeated until a termination condition has been reached. Common terminating conditions are

- Set number of iterations.
- Set time reached.
- A cost that is lower than an acceptable minimum.
- Set number of cost function evaluations.

- A best solution has not changed after a set number of iterations.
- Operator termination.

These processes ultimately result in the next-generation population of chromosomes that is different from the initial generation. Generally the average fitness will have increased by this procedure for the population, since only the best chromosomes from the preceding generation are selected for breeding.

V. GENERATION OF SUM PATTERNS

The sum patterns from discrete arrays [7] can be generated using the following expression.

$$E(u) = \sum_{n=1}^{N} A(x_n) e^{j\left[\frac{2\pi L}{\lambda} u x_n + \phi(x_n)\right]} \quad (7)$$

Here, $A(x_n)$ = Amplitude distribution

$\frac{2L}{\lambda}$ = array length

u = $\sin\theta$,

θ is the angle between the line of observer and broad side

$x_n = \frac{2n - N - 1}{N}$ = spacing function,

$\phi(x_n)$ = excitation phase distribution

VI. ARRAY OF DIPOLE ANTENNA

Dipole antennas [8] are used not only as single element but are very popular in arrays. Arrays are very versatile and are used to synthesize a required pattern that cannot be achieved with a single element. In addition they are used to scan the beam of an antenna system, increase the directivity, and perform various other functions which would be difficult with any one single element.

Radiation pattern of array [9] of Dipole antennas is given by

$$F(u) = E(\theta).E(u) \quad (8)$$

Where

$E(\theta)$ is the expression for the E-plane radiated fields and is given by

$$E(\theta) = \frac{\cos\left(\frac{\beta l}{2}\sin\theta \cos(\frac{\beta l}{2})\right)}{\sin\theta} \quad (9)$$

and E(u) is given in eq(2)

The normalized radiation patterns from array of dipoles are numerically evaluated using expressions 7 to 9 and the patterns are presented in sin θ domain. The generated radiation patterns are optimized using Genetic Algorithms to reduce side lobe levels [10] and the results are presented.

VII. RESULTS

Sum patterns generated from uniform amplitude distribution (Fig.2) and proposed amplitude distribution (Fig.3) for different number of elements in a discrete array are represented in Fig. 4 to Fig. 6. and Fig. 7 to Fig. 9 respectively. By applying the optimization technique genetic algorithm on the proposed amplitude distribution, the generated pattern's side lobe levels are further reduced. The optimized sum patterns are presented in Fig. 10 to 13 for different mutation rate and number of generations.

Sum pattern generated from array of 10 dipole elements using proposed amplitude distribution (Fig. 3) is presented in Fig. 14. The optimized radiation patterns are presented in Fig. 15 & 16 for different generations.

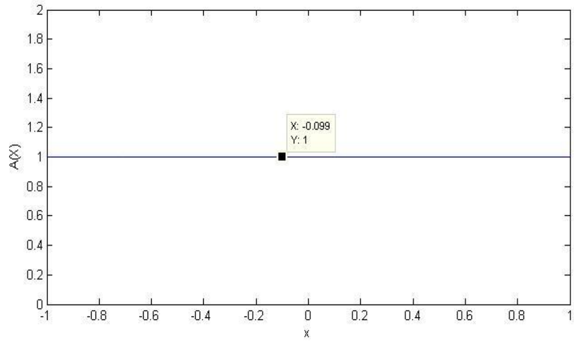


Fig. 2 Uniform Amplitude distribution

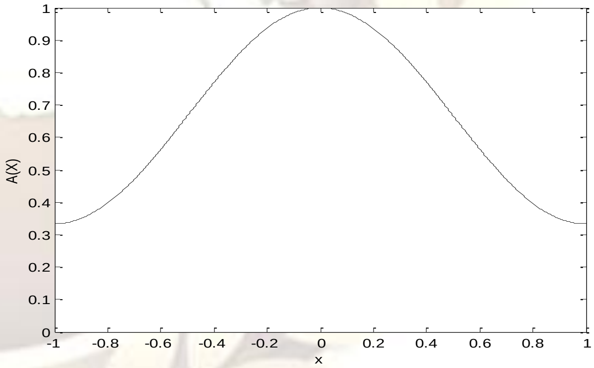


Fig. 3 Proposed Amplitude distribution

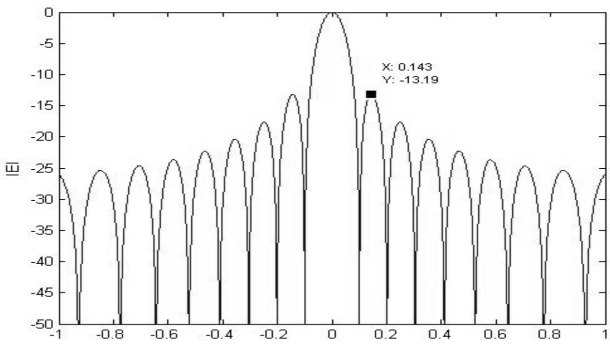


Fig. 4 Radiation pattern using uniform distribution for 20 elements

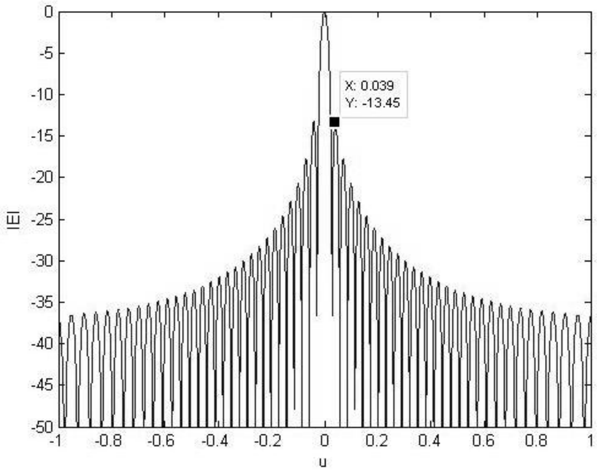


Fig 5 Radiation pattern using uniform distribution for 70 elements

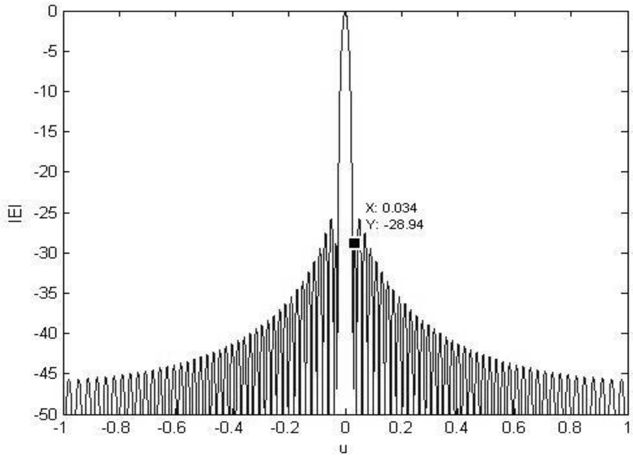


Fig. 8 Radiation pattern using proposed distribution for 70 elements

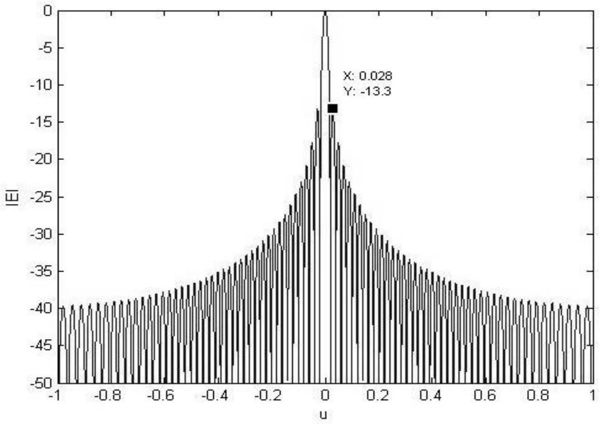


Fig 6 Radiation pattern using uniform distribution for 100 elements

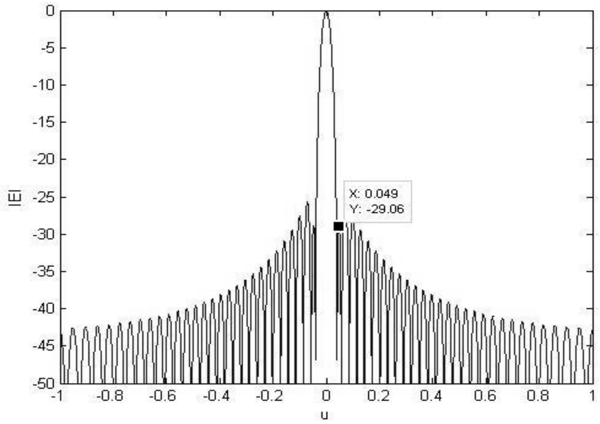
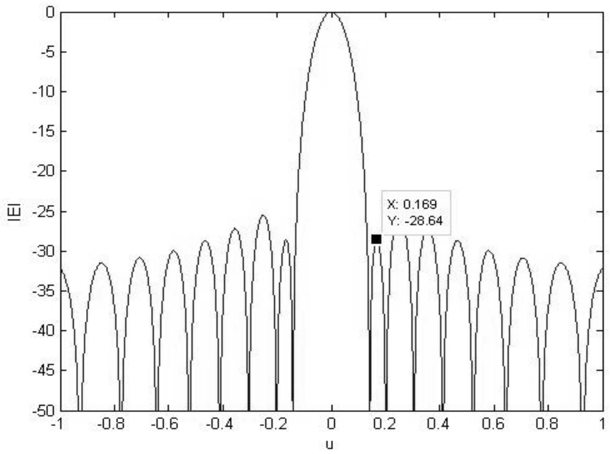


Fig. 9 Radiation pattern using proposed distribution for 100 elements



Fig, 7 Radiation pattern using proposed distribution for 20 elements

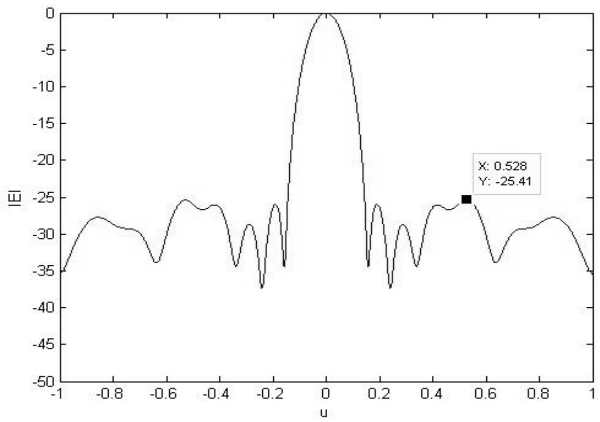


Fig. 10 Optimized pattern using uniform distribution for 20 elements, with mutation rate 0.2 for 50 Generations.

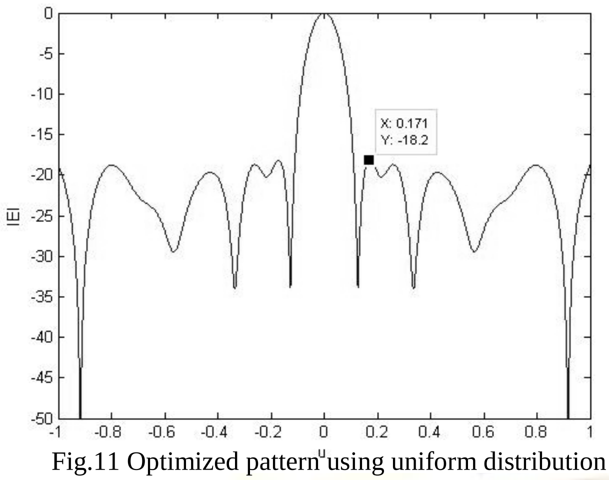


Fig.11 Optimized pattern using uniform distribution for 20 elements, with mutation rate 0.2 for 200 Generations

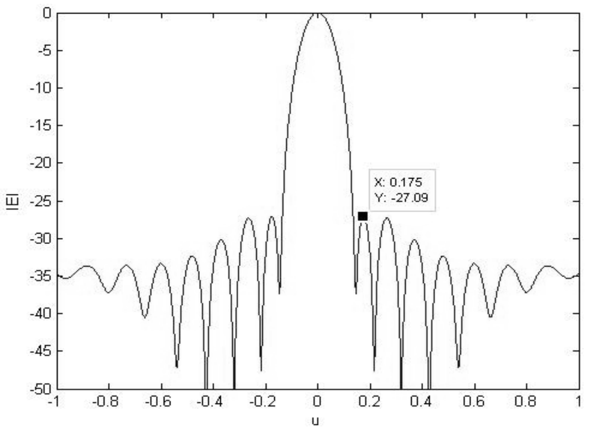


Fig. 12 Optimized pattern using proposed distribution for 20 elements, with mutation rate 0.2 for 50 Generations

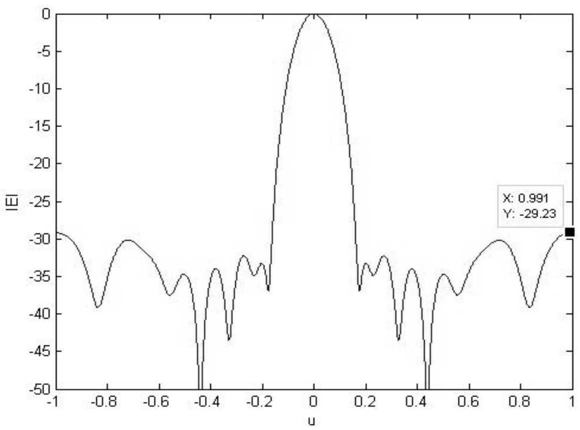


Fig. 13 Optimized pattern using proposed distribution for 20 elements, with mutation rate 0.2 for 200 Generations

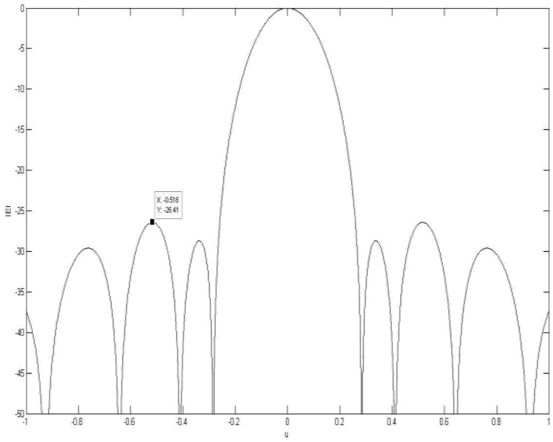


Fig. 14 Radiation pattern from array of 10 dipoles using proposed distribution

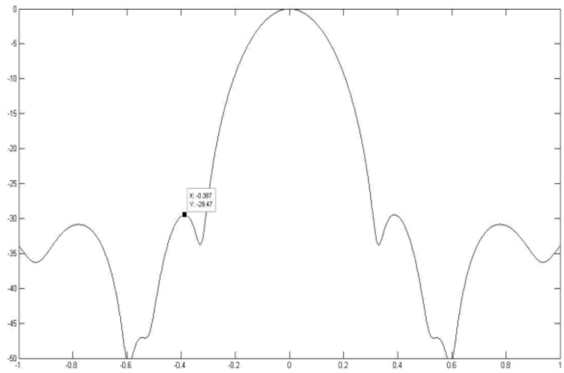


Fig. 15 Optimized radiation pattern for array of 10 dipoles, with mutation rate 0.2 for 50 Generations

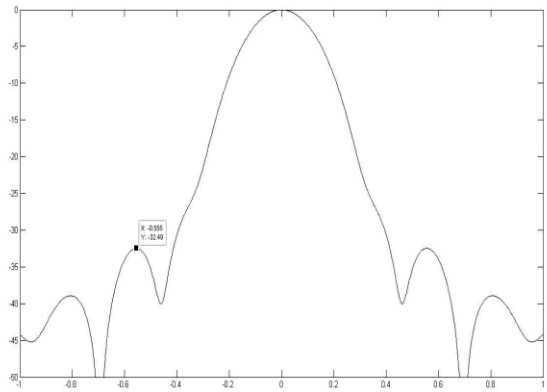


Fig. 16 Optimized radiation pattern for array of 10 dipoles, with mutation rate 0.2 for 200 Generations

VIII. CONCLUSION

Sum patterns generated from uniform amplitude distribution and proposed amplitude distribution has side lobe level of -13.45dB and -29.06dB respectively. By applying genetic algorithm and optimizing the radiation pattern the side lobe levels has further reduced significantly. It is found that the side lobe levels of sum patterns generated from array of dipoles are also reduced using Genetic Algorithm. It is observed that the beam width is increasing with decrease in side lobe levels. So it can be concluded that by using optimization techniques, the side lobe levels can be reduced. The problem of increase in beam width will be addressed in future work using suitable optimization techniques.

REFERENCES

[1]. R. L. Haupt, D. H. Werner, Genetic algorithms in Electromagnetics, Wiley-Interscience, IEEE Press, 07
[2]. R. L. Haupt, "Synthesizing low sidelobe quantized amplitude and phase tapers for linear arrays using genetic algorithms," in *Proc. Inte. Conf. Electromagnetics in Advanced Applications*, Torino, Italy, Sept.1995, pp.221-224.
[3]. Peter J.Bevelacqua and Constantine A. Balanis, "Optimizing Antenna Array Geometry for Interference Suppression", IEEE Transaction on Antenna And Propagation, Vol.55, no.3 pp 637-641,March 2007
[4]. R. L. Haupt, An Introduction to Genetic Algorithm for Electromagnetics, IEEE AP Magazine, April 1995 vol. 37, No. 2, pp 7-15.
[5]. D.E.Goldberg, "Genetic Algorithm in search optimization and machine Learning Addison-Wesley, New York, 1989.
[6]. R.L.Haupt, "Thinned arrays using genetic algorithm", IEEE Transaction on Antenna and Propagation, Vol.12 Issue 7, pp 993-999 July1994.
[7]. G. S. N. Raju, Antennas and Propagation, Pearson Education, 2005.
[8]. C. A. Balanis, Antenna Theory Analysis and Design, 2nd Edition, John Willy & sons Inc, New York, 1997.
[9]. R. S. Elliot, Antenna theory and design, prentice-hall, New York, 1981.
[10]. P. Lopez, J. A. Rodriguez, F. Ares, and E. Moreno, "Low sidelobe level in almost uniformly excited arrays," *IEE Electron. Letters*, pp.1991-1993,Nov 2000.

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