Element Failure Detection In Antenna Arrays Using Genetic Algorithm

Pinaki Mukherjee[1], #Bhaskar Gupta[2] and K. Yasumoto[2]
[1]Institute of Engineering & Management, Kolkata 700 091, India
[2]Electronics and Telecommunication Engineering Department, Jadavpur University, Kolkata 700 032, India
E-mail: bgupta@etce.jdvu.ac.in
[2]Department of Computer Science and Communication Engineering, Kyushu University, Fukuoka 812-8581, Japan.

Abstract:

Failure of one or more elements in an antenna array degrades the radiation patterns. Unless the failed element(s) is/are detected properly, no corrective measure can be adopted. Detection of the failed element(s) is often a difficult process, particularly in large arrays especially when the array is not physically accessible. In this paper, an efficient method for detecting faulty element(s) in an antenna array, based on Genetic Algorithm (GA), is proposed. This method uses a constrained optimal synthesis procedure to regenerate the degraded radiation patterns.

Keywords: Genetic Algorithm, antenna array, radiation pattern

1. Introduction

Marcano and Duran [1] proposed a method for antenna array failure correction using GA and Biswas et al [2] proposed another based on asymmetric Hopfield network model. The methods are based on changing the complex amplitude of each surviving array element until the desired radiation pattern is obtained. But the methods cannot be applied unless the failed elements are located accurately. GAs have been successfully applied to several complex electromagnetic optimization problems [3,4]. In this paper, element failure detection is treated as an optimization problem. The failed element(s) is/are detected by minimizing the difference between the degraded pattern and the pattern generated by the optimal constrained solution.

2. Genetic Algorithm

Genetic algorithm (GA) is an evolutionary search algorithm mimicking nature to yield optimal solutions to multimodal and multivariate problems [5]. GAs are computationally simple and are not limited by restrictive assumptions about the search space. There are three phases in a typical genetic algorithm optimization. These phases are (1) initiation, (2) reproduction and (3) generation replacement. Figure 1 shows a typical GA cycle. It starts with initiation consisting of filling an initial population with a predetermined number of encoded and randomly created chromosomes which represent an individual prototype solution. The reproduction phase consists of three genetic operations namely (1) selection (2) crossover and (3) mutation.

ISBN: 978-4-88552-223-9 C3055©IEICE

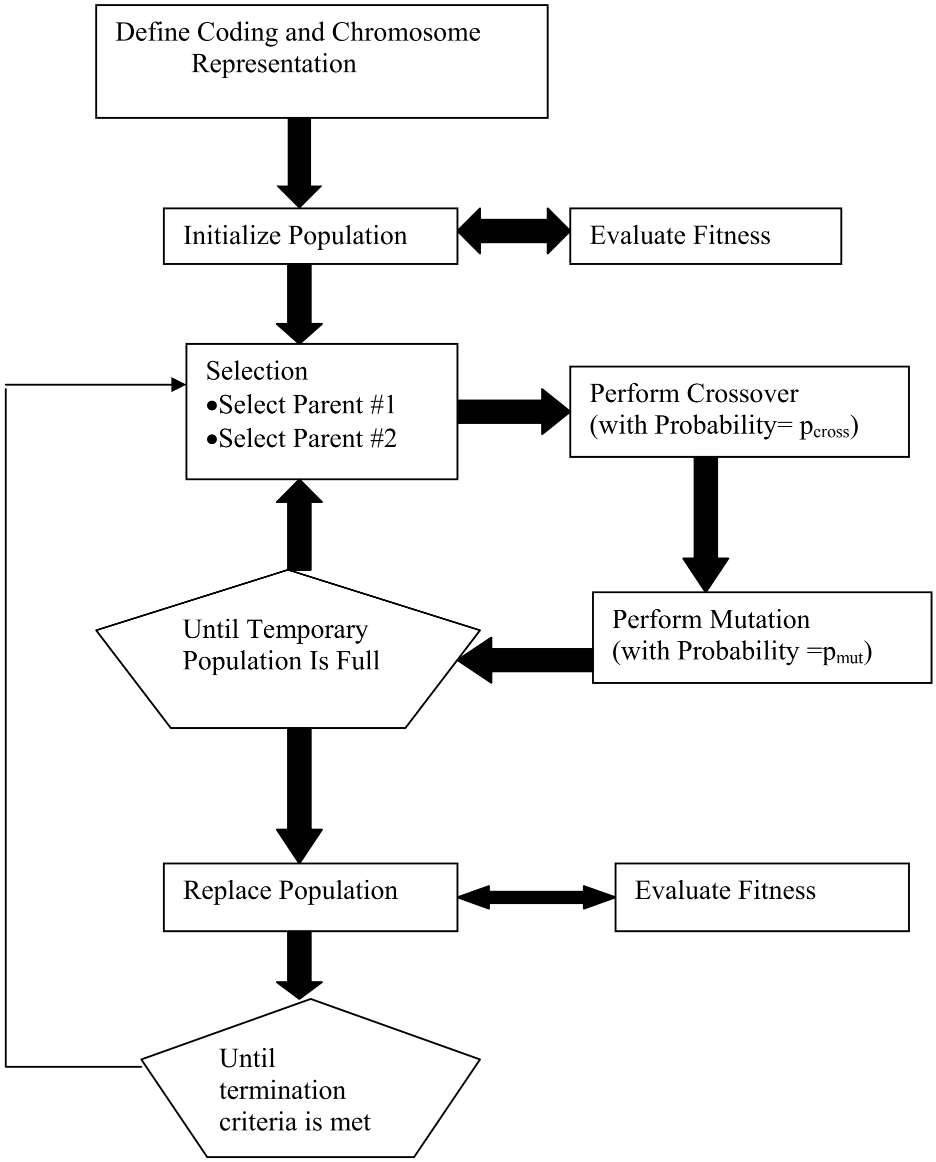

Fig.1 Block diagram of a simple genetic algorithm optimizer

3. Genetic Algorithm and Antenna Array Failure Detection

Firstly, there should be a proper mapping between the GA and the array. The relationships between elements of GA and the antenna array are tabulated below in Table 1.

Table1: Relationships between Elements of GA and the Antenna Array

Genetic Parameters	Antenna Array
Gene	One element of the array
Chromosome	One array
Population	Several arrays

The array factor of an M × N element planar array is given by

$$AF = \sum_{m=1}^{M} \left[\sum_{n=1}^{N} I_{mn} e^{j[(m-1)kd_x \sin\theta \cos\phi + \Delta\phi m,n]} e^{j[(n-1)kd_y \sin\theta \sin\phi]} \right] \quad (1)$$

where I_{mn} is the amplitude of the *mn*th element and $\Delta\phi m,n$ is the corresponding phase shift [1,2], d_x and d_y are the spacings between the elements along x and y axes.

To check correctness of the detection procedure using GA, the following steps are carried out:

1. An array (a[k]) is constructed with one or more than one predetermined elements failed and having a particular aperture distribution. The corresponding measured/simulated radiation pattern is considered.
2. Another array (b[k]) is generated with one or more elements failed. Positions and number of the failed elements are chosen randomly but the excitation pattern is kept unaltered. Array factor is calculated using eq.(1).
3. The relative error is calculated as

$$e_i=(T_i-P_i)/T_i \qquad i = 1,2,\ldots \quad (2)$$

where T_i is the relative value of the radiation pattern corresponding to a[k] and P_i is the same for b[k], each evaluated at the i-th angular position.
4. The root mean square value of the relative error is calculated as

$$E = [\sum_i |e_i|^2]^{1/2} \quad (3)$$

6. Then the fitness function, normalized between 0 (too large an error) and 1(an error equal to zero), is calculated as

$$F = 1/(1+E) \quad (4)$$

7. A population of arrays is generated randomly. Then crossover and mutation are performed on randomly selected chromosomes to obtain genetically modified individuals. Then the chromosomes are sorted according to their fitness.
8. This method is continued for a maximum preselected number of generations and repeated for a number of runs i.e. evolutionary experiments. It is stopped when the error falls below certain acceptable level. The fittest chromosome is selected at the end. It should now correspond to the binary array a[k].

In the mutation phase, a bit is randomly selected. If the selected bit is zero, it is changed to one and another bit is randomly selected and changed to zero. If the selected bit is one, it is changed to zero. Then the array is scanned and any other bit, which is zero, is changed to one.

The method was applied for planar arrays with two or more than two elements failed. Table 2 gives the parameters selected in the process. The selection of chromosomes was made according to tournament selection criterion. The inter-element spacing chosen was 0.9λ (in both x and y directions) and the radiation patterns were specified between -90° to +90° at intervals of 1°. In every case, the failed elements were detected correctly without any mistake.

Table 2: Parameters selected for GA

Size of the array	No. of failed eleme -nts	Crossover probability	Mutation probability	Chromoso -mes per generation	Max. no. of generations	Max. relative error	Average no. of iterations required for convergence
8×8	2	0.7	0.02	20	10	10^{-6}	1000
8×8	3	0.9	0.04	42	99	10^{-6}	15000
6×6	4	0.9	0.04	50	100	10^{-6}	30000

4. Conclusion

The results indicate that GA provides a more efficient and accurate alternative to direct search methods to detect failed elements in a large antenna array. In every case investigated, it is found that a direct search over the entire search space would have required a number of iterations which is about one order more than what we achieved. As expected, the difference in number of iterations required for exhaustive search and GA based search increases drastically i.e. GA becomes more and more efficient, with increase in the volume of the search space. Maximum benefit of the technique can be obtained for real life problems involving very large arrays, since the possible number of combinations of failed elements would have been extremely large in those cases. For example, failure of 4 elements in a 32 X 32 array can be due to 4.698721671e+10 different combinations. A direct computation in such cases would have been extremely time and computation resource consuming.

References

[1] D. Marcano and F. Duran, "Synthesis of antenna arrays using genetic algorithms", IEEE Antennas and Propagation Magazine, vol.42, nAo. 3, pp.12-19, June 2000.

[2] S. Biswas, P.P. Sarkar and B. Gupta, "Array factor correction using neural network model", International Journal of Electronics, vol. 91(5), pp. 301-308, May 2004.

[3] R.L. Haupt, "An introduction to genetic algorithms for electromagnetics", IEEE Antennas and Propagation Magazine, vol.37, pp.7-15, April 1995.

[4] Y. Rahmat Samii & E. Michielson, *Electromagnetic Optimization by Genetic algorithm*, John Wiley & Sons Inc., NY, 1999.

[5] D.E. Goldberg, *Genetic Algorithms in Search, Optimization and Machine Learning*, Addison-Wesley, Reading, MA, 1989.