

Comparison of Genetic Algorithm and Particle Swarm Optimization for Pattern Recovery in Failed Antenna Arrays

Rashwinder Singh, Danvir Mandal

Abstract: In an active antenna array, when a few radiating elements doesn't work due to some problem. Then the entire radiation pattern gets distorted, mostly due to increased SLL. In this paper, Genetic Algorithm is implemented and compared with Particle Swarm Optimization for linear array synthesis for far field side lobe notch using amplitude only to get the desired radiation pattern with specified SLL. Genetic Algorithm gives optimal solution of the problem than PSO. Numerical results are presented to show the effectiveness of both optimization techniques.

Index Terms: Array Antenna, beam pattern resynthesis, Transmitter/Receiver Module (TRM), failure compensation, Genetic Algorithm(GA), Particle Swarm Optimization (PSO), Beam Width First Null (BWFN) and Side Lobe Level (SLL).

I. INTRODUCTION

In wireless communication system, the antenna array is one of the most important components to improve the system capacity, spectral efficiency and data rate. It is widely used in many applications like satellite communication, sonar, mobile communication etc. for signal acquisition purpose. Generally the antenna array is made up of large number of radiating elements. Due to large number of elements, there is always a possibility of failure of one or more elements in the antenna array system. The failures of elements in the array destroy the symmetry, may cause sharp variation in field intensity across the array and distort the pattern by increasing side lobe level. This all degrades the performance of the system. Therefore, resynthesizing the optimal beam pattern is necessary to improve system performance because it is cost effective and less time consuming as compared to replacement of failed element. Secondly, in some situations like space platform the replacement of the defective element of the array is not possible. Resynthesizing the optimal beam pattern can be done by recalculating the amplitude distributions for received pattern without failed TRMs.

Many conventional techniques are proposed to solve this problem by improving the array pattern in presence of defective elements. Jung-Hoon Han *et al.* [1] proposes an algorithm for resynthesizing the optimal beam pattern from the distorted beam pattern using an adaptively weighted beam pattern mask based on a genetic algorithm. Peters [2] proposed a conjugate gradient method to reconfigure the amplitude and phase distributions.

Manuscript Received December, 2013.

Rashwinder Singh, Dept. of EEE, IET Bhaddal Technical Campus, Ropar, India

Danvir Mandal, Dept. of ECE, IET Bhaddal Technical Campus, Ropar, India

Er. M. H. Hui *et al.* [3] gave a numerical technique based algorithm to regain the directional pattern of linear antenna array with single element failure conditions. Wang, L.-L. *et al.* [4] gave a combination of genetic Algorithm and Fast Fourier Transform for array failure correction. Aydiner Taskin, *et al.* [5] proposes an algorithm for problem of linear antenna array element failure using Genetic Algorithm (GA). Rodriguez and Ares [6] proposed array failure correction for planar arrays using Genetic Algorithm and Lozano *et al.* [7] reported compensation of failed elements while maintaining fixed nulls. Beng-Kiong Yeo, *et al.* [8] proposed an algorithm based on Steering and array failure correction in digital beamforming of arbitrary arrays.

A. Linear Array Structure

The array structure used for this work is linear. In this, elements are placed on either sides of the origin at a distance $\lambda/2$ from it [5]. However, the technique can be applied to any type of array with unknown geometrical shape.

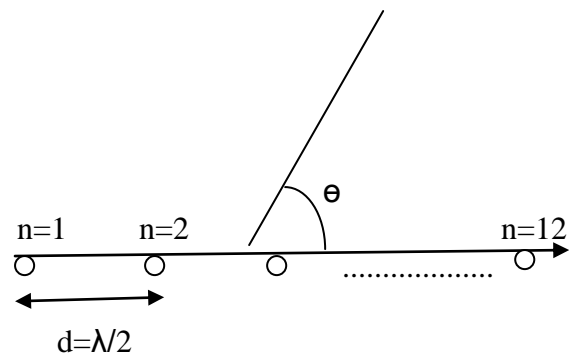


Fig.1 Schematic architecture of a symmetric Linear Antenna Array structure of 12 elements placed along x-axis

The array factor of linear array antenna with 12 antenna elements and equal distance of d can be written as equation:

$$AF = \sum_{n=1}^{12} (x_n \exp [j(n-1)\omega + \Psi_n]) \quad (1)$$

where,

x_n = current excitation of nth element

$\omega = kd \cos \theta$

d = inter element spacing

k = is the wave number

Ψ_n = driving phase of the nth element.

θ = radiating angle

B. Genetic Algorithm Overview

Genetic algorithm is a popular method of optimization being applied to many fields of endeavour, including electromagnetic.

Holland(1975) firstly introduced the Genetic Algorithms (GAs) by analogy with how biological evolution occurs in nature. If we talk about a computer program, it is a string of 1s and 0s like 100101010110110101001011..... This is similar to how chromosomes are laid out along the length of a DNA molecule. We take a binary digit as a 'gene', and a string of such genes as a digital 'chromosome'. For example, chromosome X may be 1001; Y may be 0101, etc. In a GA, an individual in the population is represented by the sequence of its chromosomes, say XYZ. According to Darwinian evolution, in a population, the fittest have a larger likelihood of survival and propagation. In computational terms, it amounts to maximizing some mathematical function representing 'fitness'.

A genetic algorithm usually encodes each parameter in a binary sequence called a gene and places the genes in an array known as a chromosome. Fitness for a chromosome is the maximum relative side lobe level in this study. Mating takes place between the best chromosomes. New chromosomes produced from mating contain parts of two parents. The fitness of new chromosomes are computed. Mutation changes some of the bits from "0" to "1" or vice versa. The algorithm stops when an acceptable solution is found or after a set number of iterations. Steps of algorithm are shown in Fig.2

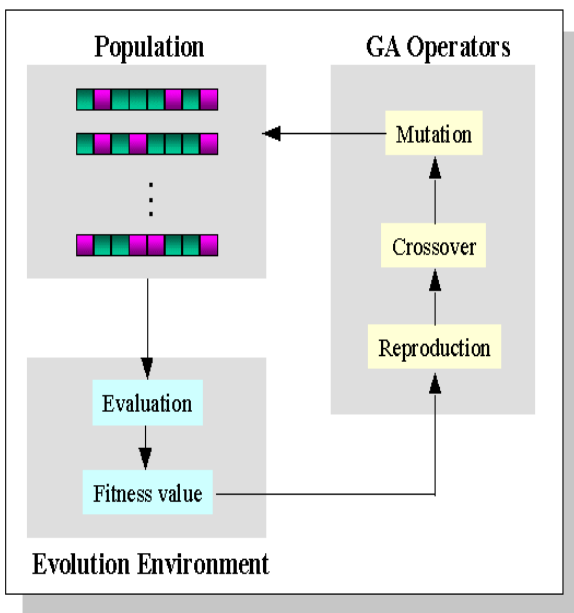


Fig.2 Steps of GA Algorithm

C. Particle Swarm Optimization

PSO is similar in some ways to genetic algorithm and evolutionary algorithms, but requires less computational bookkeeping and generally fewer lines of code. Particle Swarm Optimization (PSO) was invented by Russell Eberhart and James Kennedy in 1995 after getting inspired by the flocking and schooling patterns of birds and fishes. Originally, these two started out developing computer software simulations of birds flocking around food sources, and then they found that how well their algorithms work on optimization problems. After a number of iterations, a group of variables have their values adjusted closer to the member whose value is closest to the target at any given moment. Suppose a flock of birds circling over an area where they can

smell a hidden source of food. The one who is nearest to the food chirps the loudest and the other birds swing around in his direction. If any of the other circling birds comes closer to the target than the first, it chirps louder and the others veer over toward him. This tightening pattern continues until one of the birds happens upon the food.

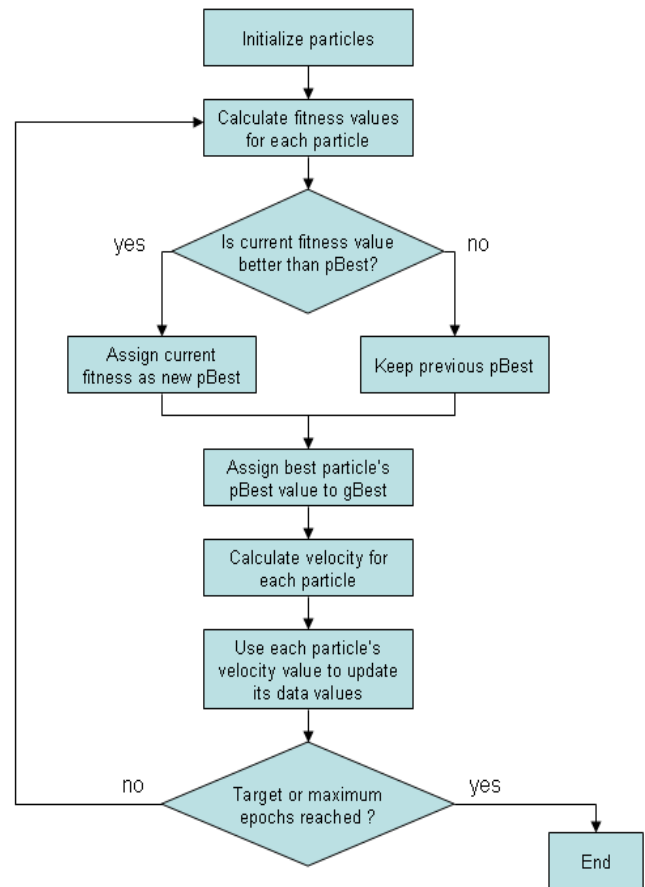


Fig.3 Steps of PSO Algorithm

The algorithm keeps track of three global variables:

1. Target value or condition.
2. Global best (gBest) value indicates that which particle's data is currently closest to the target.
3. Stopping value indicating when the algorithm should stop if the Target isn't found.

Each particle consists of:

1. Data representing a possible solution.
2. A velocity value indicating how much the data can be changed.
3. A personal best (pBest) value indicating the closest the particle's data has ever come to the Target.

The Best value only changes when any particle's pBest value comes closer to the target than gBest. Through each iteration of the algorithm, gBest gradually moves closer and closer to the target until one of the particles reaches the target.

In this paper, comparison of two optimization techniques i.e. Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) for resynthesizing the optimal beam pattern from the distorted beam pattern is made. For Computer Simulation, we assume that quantization of Amplitude distributions are made up to 6 bits, which is given by digitally controllable chips.

Section II represents the implementation of proposed algorithms. Section III will present the result comparison of both algorithms. Section IV, the last section gives the conclusion of work.

II. IMPLEMENTATION

Implementation involves two steps:

A. Implementation of GA

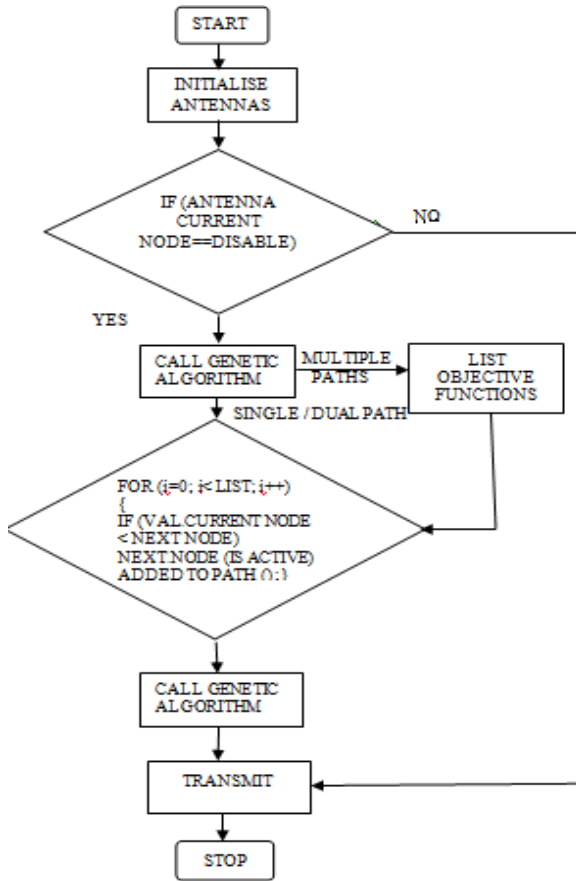


Fig.4. Flowchart of Genetic Algorithm for finding the best path in case of failure of antenna elements

According to the Fig.4, First step is to initialise the antennas. Then, we have to check whether the next node (i.e. antenna) where it is moving to be enabled or disabled. If node is disabled, then it will call the GA to find the best path for transmitting data. The best possible paths are found on the basis of several criteria's like Time, Energy, Error rate, Packet loss rate etc. From these different paths GA gives the objective function. Objective Function is finding the nodes that are suitable to all the criteria's that are mentioned above. Best paths are found, but now the objective is to find the best out of best, which is called fitness function. Fitness function gives the best route which fulfils the . This process is repeatedly done till the time of sending acknowledgment expires. So, this is the main advantage of GA that is a two time process. Firstly objectives are defined and then, Fitness function is defined from these objective functions.

The initial beam pattern assumed taken for this work has -13.39dB side lobe level (SLL) value and 6.34 degree for BWFN (shown in Fig.6). Two antennas from array of 12 elements are assumed to have failed. For implementation of

GA, we took an array of 12 antennas out of which two are failed. Then we have to calculate the Array Factor for both original and failed array using standard formula as given in equation (1). Then find the fitness function for GA using the formula:

$$Fitness\ Function = \sum_{\theta=1}^n e_i (a_1, a_2) \quad (2)$$

Where, θ = angle of deviation

a_2 = secondlevel (or node)

a_1 = firstlevel (or node)

e_i = energy of the node

where $i = 1$ to 12, because array of 12 nodes or antennas is taken in this paper.

The GA has number of iterations to reach an optimal solution. In the proposed method, the total number of iterations of the GA algorithm is divided into smaller groups called sub-iterations. The fitness function will provide the fittest value for the required problem.

B. Implementation of PSO

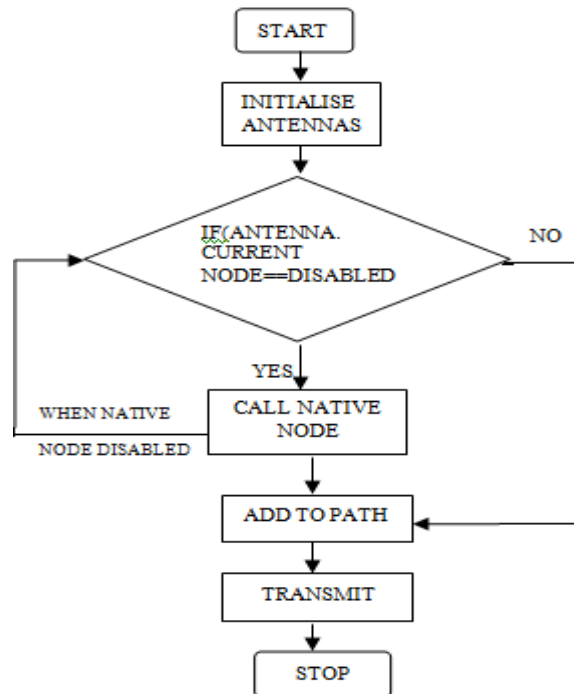


Fig.5. Flowchart of Particle Swarm Optimisation for finding the best path in case of failure of antenna elements

According to the Fig.5, Firstly initialise the antennas of array. Then, we have to check whether the next node (i.e. antenna) is enabled or disabled. If node is disabled, then PSO will call the native node and add it to the path of transmission. Native node is the best suitable node where sending node can transmit on the basis of the criteria mentioned above in GA. If the next node is not disabled, then it will add next node to the path for transmission. Now, if the native node is disabled which is being called by PSO. Then, PSO will go back to the previous state for calling new native node. So, PSO is a onetime process. It doesn't define the objective functions first. It gives directly the fitness function for the optimal path.

In first step of implementation of PSO is to take the parameters that are required for optimisation. Firstly, we have to calculate the value of Array Factor for both failed and original Array using standard formula given in equation (1). Then fitness function is given by equation:

$$Fitness\ function = \sum_{\theta=1}^{\theta=n} e_i(a_j) \quad (3)$$

where, a_j = path node which has been selected
 n = total number of nodes (i.e.12)
 θ = angle of deviation

In the present work of PSO, 12 initial particles were taken and they were manipulated according to the following equation:

$$V_{n+1} = wv_n + c_1rand()(P_{best,n} - x_n) + c_2rand()(g_{best,n} - x_n) \quad (4)$$

where, v_n is the velocity of the particle in the nth dimension and x_n is the particle's coordinate in the nth dimension. The parameter w is the initial weight that specifies the weight by which the particle's current velocity depends on its previous velocity. P_{best} and g_{best} are the personal-best and global-best respectively. c_1 and c_2 are two scaling factors which determine the relative pull of P_{best} and g_{best} . $rand()$ is a random function in the range [0, 1]. Once the velocity has been determined it is easy to move the particle to its next location. The velocity is applied for a given time-step Δt and the new coordinate x_n is computed as

$$x_{n+1} = x_n + \Delta t \times v$$

During this iterative process, the particles gradually settle down to an optimum solution.

III. RESULTS & DISCUSSIONS

Both techniques are applied to the problem of resynthesis of antenna radiation pattern. Results are shown in form of radiation pattern and values of SLL and BWFN are shown in tables.

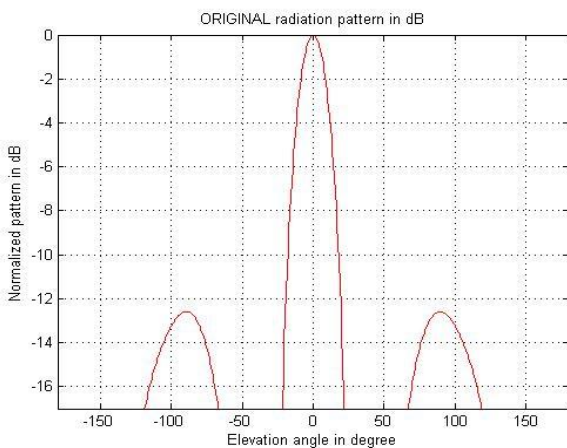


Fig.6.Original Antenna Array Pattern for 12 antenna elements

Table 1. Antenna array of 12 elements with corresponding values of SLL and BWFN

S.No.	Total number of elements	SLL(dB)	BWFN (degree)
I	12	-10.23	7.23

I	12	-13.39	6.34
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For the implementation of the developed methodology, a 12-element linear array with $\lambda/2$ inter-element spacing is taken as the test antenna. Standard analytical procedure was applied to find the non-uniform excitations of a 13.39dBsidelobe level (SLL) and 6.34 degree BWFN in the Linear array as shown in Fig. 6. The Table 1. represents antenna array of 12 with its corresponding values of SLL and BWFN.

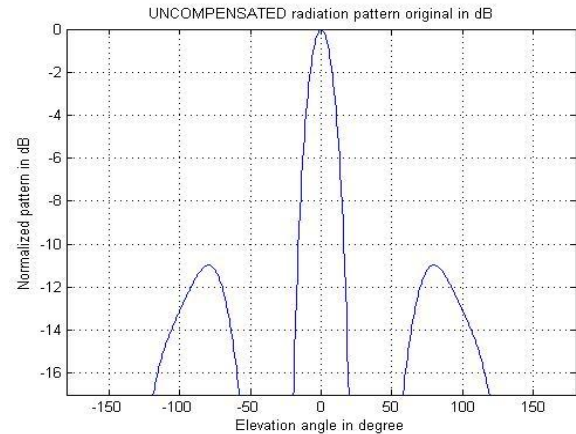


Fig.7. Distorted Antenna Array pattern after failure of 2 elements out of array of 12 elements using GA

Table 2. Uncompensated values of SLL and BWFN for antenna array of 12 elements using GA

S.No.	Total number of elements	SLL(dB)	BWFN (degree)
I	12	-10.23	7.23

The above Fig.7 shows the antenna array pattern after the failure of two elements out of 12 elements. The SLL increases upto a value -10.23dB and BWFN increases upto value 7.23, which degrades the performance of system. Table 2. shows the distorted values of SLL and BWFN for antenna array of 10, when two elements fails.

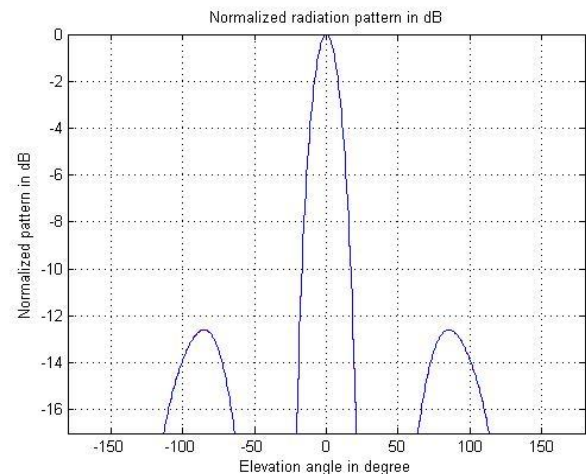


Fig.8. Array pattern recovered after failure of two elements out of 12 elements using GA

Table 3. Compensated values of SLL and BWFN for antenna array of 10 elements

S.No.	Total number of elements	SLL(dB)	BWFN (degree)
I	10	-13.11	6.53

In this present approach of compensation for the failure of elements in antenna array was performed by re-optimizing the amplitude and phase excitations of only 10 elements. It recovers the antenna array pattern with SLL and BWFN at -13.11dB and 6.53 degree respectively as shown in Fig.8. Table 3 represents values of SLL and BWFN for antenna array of 10 elements, which are recovered after failure of two elements using GA.

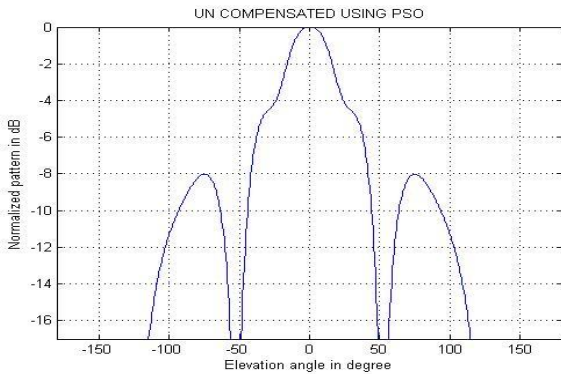


Fig.9. Distorted Antenna Array pattern after failure of 2 elements out of array of 12 elements using PSO algorithm

Table 4. Uncompensated values of SLL and BWFN for antenna array of 10 element

S.No	Total number of elements	SLL(dB)	BWFN (degree)
I	12	-8.23	9.12

Fig.9 represents the distorted or uncompensated antenna array pattern after failure of two elements out of 12 elements when we are using PSO algorithm to resynthesize the distorted pattern.

Table 4. represents uncompensated values of SLL and BWFN for antenna array of 10, when two antennas from antenna array of 12 gets failed.

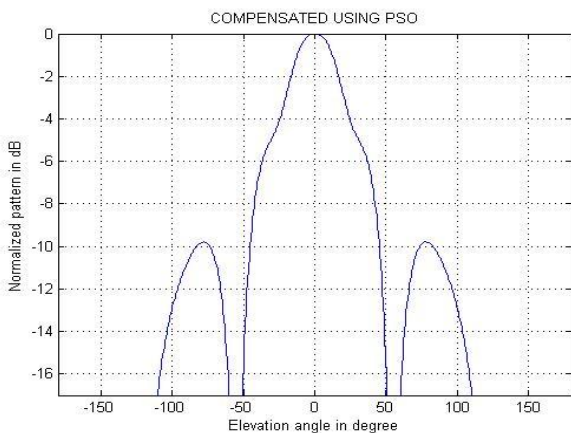


Fig.10. Antenna Array pattern recovered after failure of two elements out of 12 elements using PSO

Table 5. Compensated values of SLL and BWFN using PSO algorithm

S.No.	Total number of	SLL(dB)	BWFN(degree)
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	elements		
I	10	-10.11	8.61

In this case efforts were made to reduce the SLL of the damaged pattern due to element failure in antenna array by perturbing the amplitude and phase excitation of only 10 elements. The corrected far field pattern is shown in Fig.10. The recovered pattern in this case has SLL of -9.76db & BWFN of 15.10. Table 5. represents compensated values of SLL and BWFN using PSO algorithm in array of 10 elements, after failure of two elements.

IV. CONCLUSION

The synthesis of amplitude for a far-field side lobe envelope has been done for both GA and PSO. GA shows better results in reduction of SLL, when two elements from an antenna array fails. Although in real time applications, GA has high iteration time. But, flexibility and ease of solution makes it worth for future applications. Hence, Genetic Algorithm has executed successfully to work on the linear array synthesis problem.

REFERENCES

- Jung-Hoon Han ; Sang-Ho Lim ; Noh-Hoon Myung, " Array Antenna TRM Failure Compensation Using Adaptively Weighted Beam Pattern Mask Based on Genetic Algorithm " Antennas and Wireless Propagation Letters, IEEE Volume: 11
- T. J. Peters, "A conjugate gradient based algorithm to minimize the sidelobe level of planar arrays with element failures," IEEE Trans. Antennas Propag., vol. 39, no. 10, pp. 1497-1504, Oct. 1991.
- Er. M. H. Hui et al. gave a numerical technique based algorithm to regain the directional pattern of linear antenna array with single element failure conditions
- L. L. Wang and D. G. Fang, "Combination of genetic algorithm and fast fourier transform for array failure correction," in Proceedings of the 6th International Symposium on Antennas, Propagation and EM Theory, Beijing, China, November 2003.
- Aydiner Tankin and Cigdem Seekin Gurel, "Antenna Array Pattern Optimization in the case of array element failure" 33rd European Microwave Conference Munich, pp. 1083-1086, 2003.
- J.A. Rodriguez, F. Ares, E. Moreno, "GA Procedure for Linear Array Failure Correction", Electronics Letters, 36, pp. 196-198, 2000.
- M. V. Lozano, J. A. Rodríguez, and F. Ares, "Recalculating linear array antennas to compensate for failed elements while maintaining fixed nulls," J. Electromagn. Waves Appl., vol. 13, pp. 397-412, 1999.
- Beng-Kiong Yeo and Yilong Lu, " Adaptive Array Digital Beamforming Using Complex-Coded Particle Swarm Optimization-Genetic Algorithm" APMC2005 Proceedings, 0-7803-9433-X/05/\$20.00 ©2005 IEEE.
- T. Panigrahi, A. Patnaik*, S. N. Sinha, C. G. Christodoulou, "Amplitude Only Compensation for Failed Antenna Array Using Particle Swarm Optimization" 978-1-4244-2042-1/08/\$25.00 ©2008 IEEE
- C. A. Balanis, Antenna Theory: Analysis and Design, John Wiley & Sons, Inc., 1997
- J. Robinson and Y. Rahmat-Samii, "Particle Swarm Optimization in Electromagnetics," IEEE Trans. Antennas and Propagat. vol. 52, no. 2, pp. 397-407, 2004.
- R. C. Eberhart and Y. Shi, "Comparison between genetic algorithms and particle swarm optimization," in Proc. 7th Annu. Conf. Evol. Program. (EP-98), vol. 1447, Lecture Notes in Computer Science, Mar. 1998, pp. 611-616.
- Mohd. Tarmizi Ali, Azita Laili Yusof, Norsuzila Ya'acob, "A Reconfigurable Antenna Array (RAA) Integrated with RF Switches," "Research Management Institute (RMI) University Teknologi Mara 40450 Shah Alam, Selangor Malaysia, January 2012.