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Design of 8-Elements Linear Dipole Antenna Array to Suppress Sidelobe Signals by Using Genetic Optimization

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Keywords

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Abstract

High sidelobe levels can result in unwanted interference or "noise" from signals arriving from directions other than the desired main lobe. These signals can degrade the overall performance of a system by reducing the signal-to-noise ratio, making it more difficult to distinguish the intended signal from background noise. In systems like radar or satellite communication, sidelobes can cause interference to other users or systems operating in adjacent frequency bands or directions. Suppressing the sidelobes helps minimize this cross-talk and interference. When the sidelobes are suppressed, more of the transmitted power is concentrated in the main lobe, improving the efficiency of power usage. This is important in communication systems where conserving power is essential, such as in satellites or mobile devices. In environments where signals may bounce off objects (such as in urban areas for wireless communication or radar), sidelobes can pick up signals reflected from various surfaces. By suppressing sidelobes, the system becomes less susceptible to multipath interference, which can degrade signal quality and accuracy. To sum up, sidelobe suppression is crucial for ensuring the efficiency, accuracy, and reliability of many systems, particularly in radar and communications. It minimizes interference, reduces false detections, improves directional sensitivity, and ensures that resources (e.g., power and bandwidth) are used effectively. In this paper, 8-element linear dipole antenna array designed to suppress sidelobe signals, which causes interference on the communication system. One of the key parameter is the distance between the each antenna. In this simulation, we defined the distance between each antenna as 0.6*lambda, for 3GHz operating frequency. Another optimization parameter is the magnitude of each antenna element, aimed to optimize magnitudes of each antenna element's sidelobe levels by using Genetic Algorithm (GA), where theta angle between 40-60 degrees. The antenna array design done in CST Studio environment, but amplitude tuning with GA performed using MATLAB. We compared our design results for each simulation, observed the change of directivity for antenna array by using GA. As a result, the sidelobe level between the desired theta 40 and 60 degrees suppressed from -17dB to -28.2dB but it observed that the directivity of the main antenna radiation pattern decreased from 13dBi to 10dBi.

Cite

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1. INTRODUCTION

The radiation of antennas produces some undesirable effects, such as side lobe level (SLL). In most antenna array applications, especially the first SLL is an undesirable effect because it causes too much electromagnetic interference (Liang et al., 2017). Due to emerging high frequency techniques, SLL suppression is a very important issue for antenna arrays operating in the FR1 and FR2 region. The main parameters of a selected antenna model (radiation pattern, impedance, half power beamwidth, main bandwidth, directivity, radiation

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efficiency etc.) are calculated by methods known in the literature (Panduro et al., 2006). The main objective of antenna array analysis is to determine the number of antenna array elements and the spacing between antenna elements that can produce the expected radiation pattern for the center operating frequency with the best approximation and maximum directivity (Katoch et al., 2021).

In general, antenna pattern studies are classified into the three main groups. The first group is the studies that generate radiation diagrams with zeros in predetermined directions. An example of the first group is the Schelkunoff method. The second group includes the design of an antenna that can approximate the desired radiation pattern over the entire visible region. Woodward and Fourier transform by Taylor (1955), are the techniques used for this purpose.

The third group includes techniques that produce radiation patterns with narrow main beam and low side auricle levels. Binomial method by Taylor (1955), Dolph-Chebyshev by Taylor (1955) are examples of this third group.

In the literature, the tuning of main beamwidth and sidelobe levels has been frequently emphasized for pattern shaping in array antennas. For example, Dolph calculated the excitation coefficients of the equally spaced array elements that give the minimum main beamwidth for a given maximum sidelobe level, showed that radiation diagrams with equal sidelobe levels obtained with these coefficients can also be obtained with Chebyshev polynomial, developed a new formulation for the design of Chebyshev arrays that expresses the array factor in terms of cosine and hyperbolic-cosine functions without using Chebyshev polynomials directly (Satılmış, 2022).

The genetic algorithm, used as an improvement method in the study of sequence analysis, is one of the so-called heuristic algorithms, algorithms that include rules based on experience and training. The concept of genetic algorithm is inspired by the science of genetics. There are several studies in the literature where genetic algorithms have been used for antenna pattern synthesis, most of these studies have used linear arrays. For example, organized the placement of linear array elements using a genetic algorithm. In subsequent studies, calculated the antenna amplitude excitation coefficients for linear antennas for pattern shaping using a genetic algorithm (Lambora et al., 2019; Aydin & Erdem Aykac, 2023; Zhang & Li, 2023). More traditional optimization methods such as particle swarm optimization and ant colony algorithm generally used to suppress the side lobe levels of antenna arrays, with the developing artificial intelligence applications, sidelobe suppression techniques with increased accuracy are also used (Yang et al., 2021; Xiang et al., 2024).

In this study, Genetic Algorithm (GA) is selected to optimize the amplitude parameters of linearly spaced antenna arrays, while keeping the distance between antennas constant. In this antenna array design, since all antennas are positioned at equal distances, genetic optimization is only applied on the radiation amplitudes of the antennas (Singh et al., 2022; Nie et al., 2024; Xiang et al., 2024). In this way, it is aimed to calculate the optimum radiation amplitudes for each antenna. For the antenna radiation amplitude calculation, the optimum value of the radiation amplitude is calculated with a coding in MATLAB, as a matrix form.

In this case, the antenna radiation amplitudes are optimized using the genetic optimization algorithm. With the new antenna radiation amplitude values obtained, the antenna array designed on CST Studio is updated and the radiation directivity of the new radiation amplitude and the suppression at the side lobe level are evaluated. The array of 8 dipole antennas positioned in the x-axis with a distance of 0.6*lambda between them is designed using the CST Studio Suite program. For the 3 GHz center frequency, the lambda value was calculated as 96 mm with an optimization margin of 4.5% and the 0.6*lambda distance was defined as 57.60 mm (Aydin & Erdem Aykac, 2023).

2. MATERIAL AND METHOD

The genetic algorithm was developed by J. H. Holland, showed that complex structures can be coded using simple data sequences. The genetic algorithm (GA) is an optimization algorithm inspired by natural selection; it is a method for solving optimization problems based on a natural selection process. Genetic algorithms act as a biological metaphor and use some of the methods observed in natural evolution (Dhiman & Kaur, 2019; Ma et al., 2019). GA aims to yield solutions for the consecutive generations (Lambora et al., 2019). Genetic algorithms are widely used to generate high-quality solutions to optimization and search problems based on biologically inspired operators. Once the genetic representation and fitness function defined, a GA proceeds to initialize a population of solutions and then evolve it through repeated application of mutation, crossover, inversion and selection operators. GA changes the process of searching for the optimum solution adaptively, check the probabilities and reaches the optimal solution.

The main advantage of genetic algorithms is that they do not require any knowledge of the general nature of the problem they are trying to optimize. They can easily find an ideal general solution in a complex multidimensional search space. Genetic algorithms are particularly effective in finding the approximate maximum or minimum value in a high-dimensional, multi-model function set.

The fitness function defined on the genetic representation and measures the quality of the represented solution. GA can be applied to the genetic algorithm to solve problems which are not well suited with standard optimization algorithms, including problems where the objective function is discontinuous, non-differentiable, stochastic or highly nonlinear. It uses a group search technology and the evolutionary population represents a set of problem solutions such as increasing data rate, reducing power consumption, optimize interference effect of communication channel and improving spectrum efficiency (Liang et al., 2020; Durmus & Kurban, 2022).

The flow diagram of a simple genetic algorithm is given in Figure 1. In the algorithm, an initial population is first created, then genetic processors are used to generate the solutions in the next generation through reproduction, crossover and mutation. The fitness assessment process is applied to each individual in order to perform the selection process applied during the reproduction event. The cycle of development and evaluation of successive generations continues until the best solution is found. A simple genetic algorithm consists of five basic steps. Each of these significantly affects the performance of the algorithm (Liu et al., 2014; Durmus & Kurban, 2022).

These steps are:

a. Representation of solutions
b. How to create an initial ensemble
c. Fitness or quality assessment criteria
d. Genetic processors
e. Control parameters

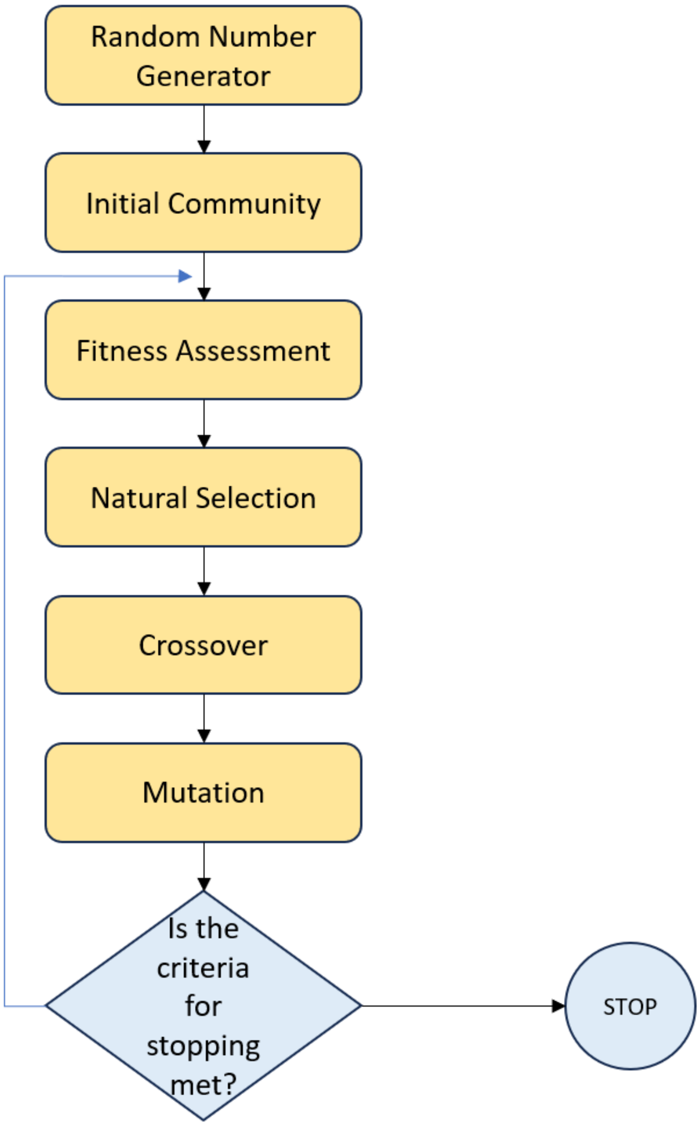


Figure 1. *A simple flowchart of a genetic algorithm*

The genetic algorithm differs from the classical, derivative-based optimization algorithm in two main ways, as summarized in Table 1.

Table 1. *Comparison between the Classical Algorithm and Genetic Algorithm*

Classical Algorithm	Genetic Algorithm
It generates a single point in each iteration. The sequence of points converges to the optimum solution.	In each iteration, a point forms the population; the best point in the population is an optimal solution.
It selects the next point in the sequence with a deterministic calculation.	It selects the next population through computation using random number generators.

The basic control variables of a simple genetic algorithm are density size, crossover and mutation rate. The density of a genetic algorithm affects its performance in two ways. Reducing the density will lead to under-sampling, making divergence difficult to achieve and the search will drift towards a sub-optimal point. Conversely, if the number of densities is too large, a one-generation evolution will require a very long time. This is especially undesirable when solving real-time problems. According to the simulation results, the population size is set to 512 in this study to achieve the best directionality on radiation pattern.

Mutation is an important as it allows new regions to enter the search space. The mutation rate should be well controlled to design an efficient genetic algorithm. For example, a high mutation rate will introduce randomness into the search, which will divergence processes too quickly. Conversely, a very low mutation rate will reduce the divergence too much, causing the search to find a non-ideal point as a solution. Therefore, the mutation rate is set to 0.01 in this study. The crossover rate is a parameter used to determine the frequency of the crossover processor applied to the structures (individuals of the density). A low crossover rate will cause too few new structures to enter the generation, making the algorithm inefficient and the search will become bogged down at a certain point. A high crossover rate will cause the search space to be explored very quickly, thus reducing the performance of the algorithm. In this study, the crossover rate is used as 0.5 to get optimum achievement.

3. ANTENNA ARRAY STRUCTURES AND APPLICATIONS

Antenna arrays are antenna systems formed by combining different or similar antennas in different ways. The first practical use of arrays was realized in 1937 in the light of previous work in this field. Studies in the literature show that antenna arrays can produce radiation patterns with desired characteristics by adjusting the amplitude and phase of the feed applied to the antennas. If all antennas in the array are fed in the same phase, the main beam of the radiation diagram is perpendicular to the array plane. In other cases, the main beam can be oriented in different directions such as θ1, θ2, θ3. Since the phases can be changed electronically, the main beam can be formed in any desired direction within the field of view defined by the radiation pattern of the antennas in the array (Amaireh et al., 2019).

In general, the radiation diagram of a single element has large apertures and each element provides a low gain. In most applications it is necessary to design antennas with very high gain for long distance communication. The high gain is proportional to the physical structure of the antenna. Increasing the size of the individual elements can provide higher gain. Another way to increase the gain of the antenna without increasing the size of the individual elements is to match the radiating elements with the appropriate electrical and geometrical structure. This new antenna consisting of multiple elements is called an array. In most applications, the elements of the array are chosen identically. In order to obtain high gain radiation diagrams, it is necessary to add the element areas in the desired directions and cancel each other in the remaining directions, but this is difficult to achieve in practice. The factors affecting the total radiation pattern of the antenna in an array of identical elements are as follows (Taylor, 1955):

a. Geometric structure of the entire array (linear, circular, etc.)
b. Distance between antenna elements
c. Excitation amplitudes of elements
d. Excitation phases of elements
e. Radiation diagrams of elements

N elements in the array can be placed with N-1 different range values, as shown in Figure 2.

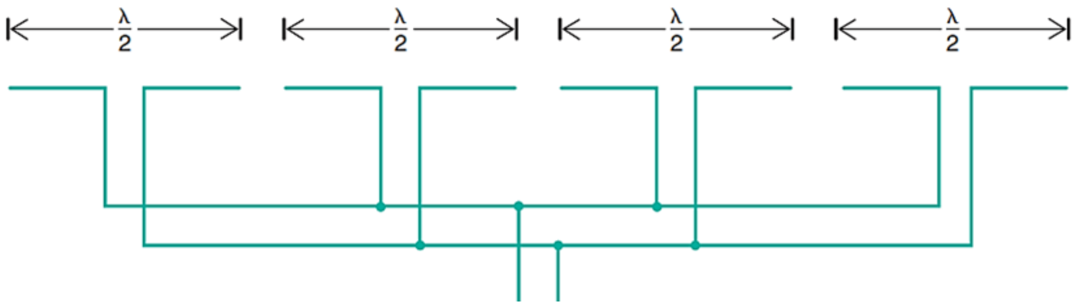


Figure 2. *Linear λ/2 dipole antenna array structure*

In this antenna array design, since all antennas are positioned at equal distances, genetic optimization is applied on the radiation amplitudes of the antennas, aimed to calculate the optimum radiation amplitudes for each antenna, by using 8-element antenna array shown in Figure 3.

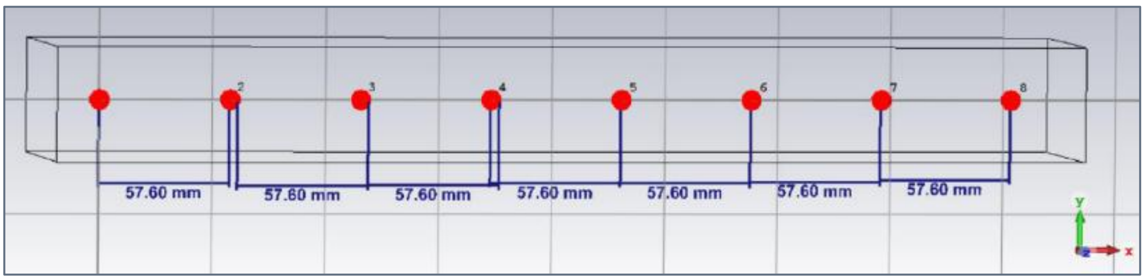
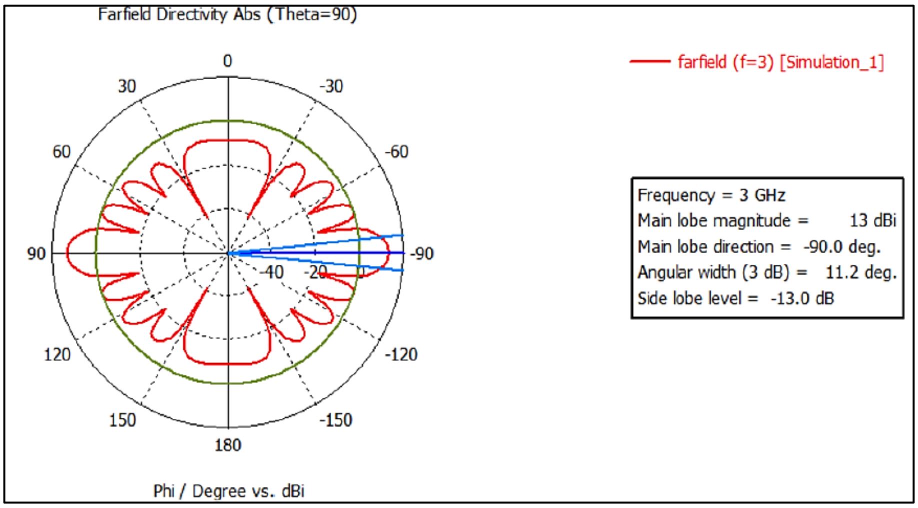


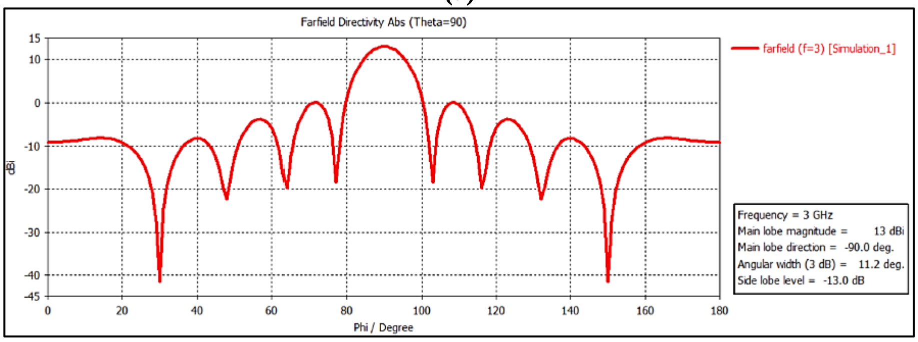
Figure 3. *Linear antenna array structure*

4. RESULTS AND DISCUSSION

The radiation pattern of dipole antenna arrays can be plotted on a 2D graph with axes ϴ (theta) and φ (phi) or on a 3D graph in cartesian coordinate system. The cartesian and polar representations of the far-field radiation obtained at a central operating frequency of 3GHz shared in Figure 4.



(a)



(b)

Figure 4. a) *Polar representation of the far-field radiation,* ***b)*** *Cartesian representations of the far-field radiation*

In the Matlab environment, genetic calculations have been performed to calculate updated amplitude values for the new pattern, and an attempt has been made to simulate them. Since the number of elements is 8, the N value has been updated to 8. Correspondingly, in order to meet the dimensions, the A amplitude matrix has also been updated and defined as a matrix with 8 elements, all having an amplitude of 1.

N=8;

A= [1 1 1 1 1 1 1 1];

D= [0.576 1.152 1.728 2.304 2.88 3.456 4.032 4.608];

The radiation pattern of an 8-element planar dipole antenna array shared in Figure 5. As can be understood from this graph, for the value of theta between 40 and 60 degrees, the side lobe level we want to suppress is approximately around -17 dB.

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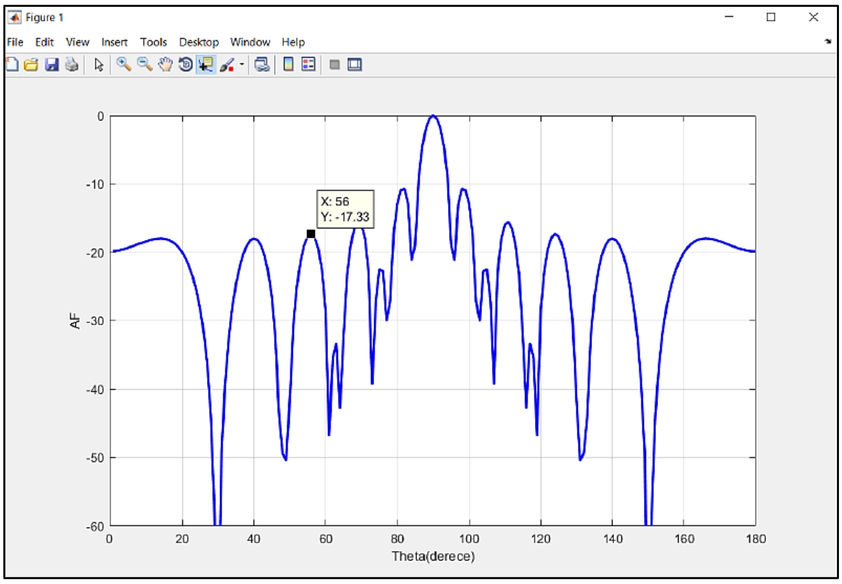


Figure 5. *The radiation pattern of an 8-element planar dipole antenna array in MATLAB*

It has been determined that the best side lobe value that can be obtained using genetic algorithm optimization for the existing side lobe between 40 and 60 is -28.2 dB. The results of the genetic algorithm run shown in Figure 6.

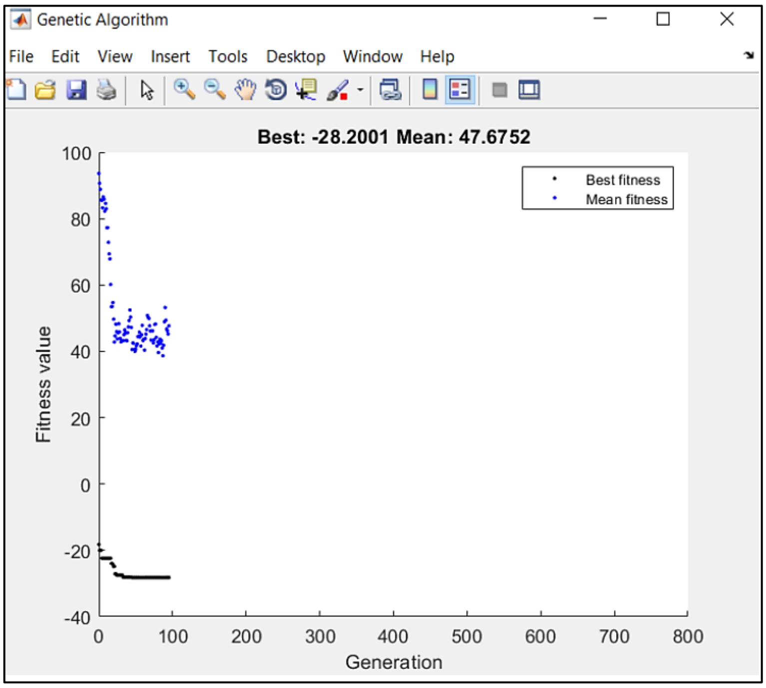
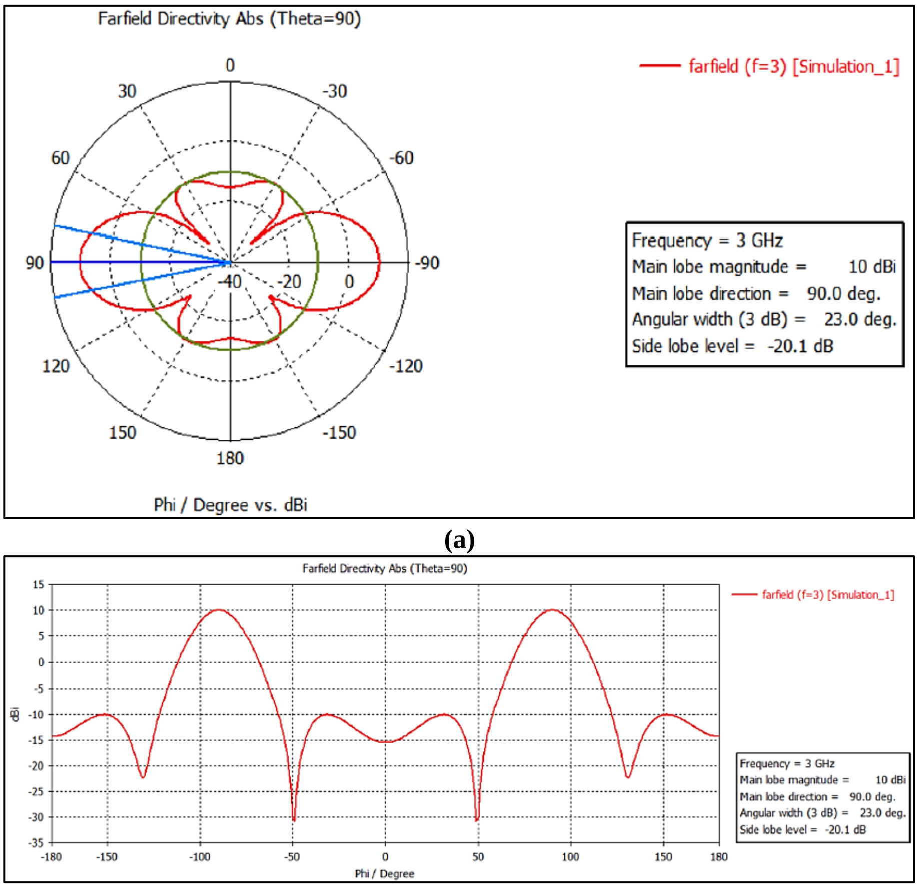


Figure 6. *Results of the genetic algorithm in MATLAB*

The values belonging to the new generated matrix [B] obtained with the genetic algorithm are shared.

B=[1.11 -0.92 5.83 9.49 11.13 4.13 1.78 -0.14];

The far-field radiation of the optimized amplitude values obtained at the working frequency is shown in Cartesian and polar representation in Figure 7.



(a)

(b)

Figure 7. a) *Polar representation of the far-field radiation,* ***b)*** *Cartesian representations of the far-field radiation*

5. CONCLUSION

In this study, GA algorithm is used to suppress side lobe signals for 8-element linear dipole antenna arrays. The 8-element linear dipole antenna array is designed using CTS Studio and GA optimization is implemented in Matlab. As can be seen from the cartesian representation in Figure 4, multiple dominant sidelobe signal levels are observed in the system with a center operating frequency of 3GHz.

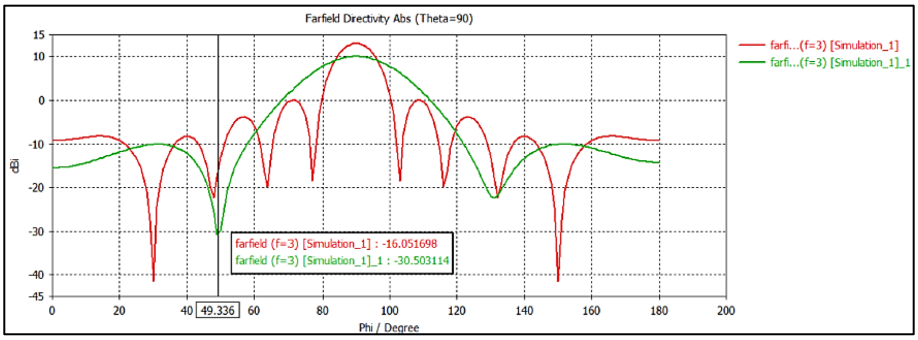
The Matlab representation for the case where the phi angle is varied between 40 and 60 degrees is shown in Figure 5. With the Genetic Optimization algorithm applied to the model, the new amplitude matrix [B] was obtained. The iterations of this GA learning are shown in Figure 6, best value detected around -28dB.

The conclusions regarding the overlapping of the initial state and the optimized radiation patterns are shown in Figure 7. According to the results obtained, the side lobe level has been suppressed with the new amplitude values, but the main lobe directivity has weakened by approximately 3 dB, and the beam width (BW) has increased.

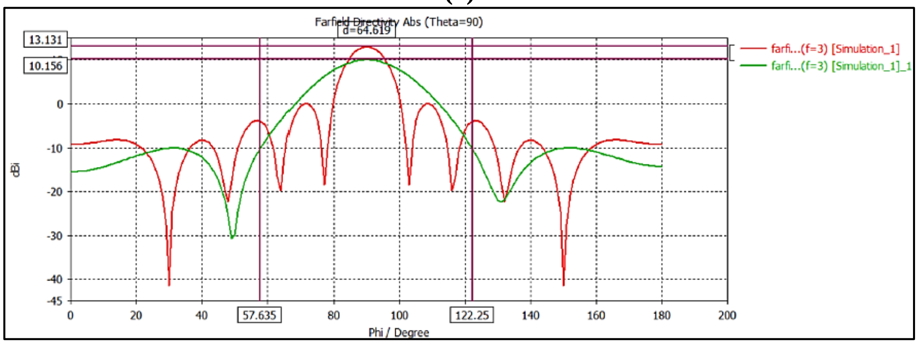
Initial Condition BW: 24 degrees

Optimized Amplitude Value BW: 64 degrees

As a result, the desired theta has been suppressed from -17 dB levels to -28.2 dB levels in the side lobe level occurring between 40-60 degrees. However, it has been observed that the directivity value of the main radiation pattern has decreased from 13 dBi to 10 dBi as shown in Figure 8.



(a)



(b)

Figure 8. a) *Directivity comparison of initial and optimized design,* ***b)*** *Optimized beamwidth measure*

Literature researches shows that the use of the Genetic Optimization algorithm with linear array antennas gives more efficient results compared to the use of planar and circular antenna arrays. When the radiation diagram obtained by re-arranging the distance between antennas with Genetic Optimization is examined, it is observed that it has the versatility that can be achieved with more complex systems both in terms of the number of iterations and the average crossover rates. In applications where beam directivity is not a primary parameter, suppressing side lobe signals by using genetic optimization provides a useful solution.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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