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Research Article

Multi-objective concurrent optimization of antenna array parameters for 5G applications

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Abstract
Fifth generation (5G) mobile networks require highly directional beams to serve its users. The basic requirement of beamforming techniques used in 5G is to generate narrow beams with lowest side lobe level (SLL) possible. SLL indicates the concentration of radiated energy in an undesired direction, which leads to power wastage as well as interference with other radiating elements. SLL can be considerably reduced by various methods which include amplitude tapering and different optimization techniques. Tapered excitations reduce the side lobes but increase the beam width. Optimization techniques can be applied to different antenna parameters to achieve reduced SLL without compromising on beam width. Also, these techniques are effective on large arrays. This paper presents and compares elemental excitation optimization and spacing optimization for linear antenna arrays (LAA), using genetic algorithm (GA). Array sizes of 16 and 64 are considered and the excitation amplitudes as well as spacing between elements are varied to achieve reduced SLL. Increase in array size from 16 to 64 resulted in narrower beams as well as reduced SLL, while amplitude and spacing controls improved overall SLL-beam width tradeoff. Spacing control method has performed better than the amplitude-control method in reducing SLL for 16-element and 64-element arrays. Apart from SLL, the half-power beam width (HPBW) is also measured for the optimized arrays, which ensures better concentration of radiated power in desired direction. Compared to the amplitude-control method, HPBW is lowered in spacing control method. To simultaneously reduce SLL and beam width, which are conflicting parameters, multi-objective genetic algorithm (MO-GA) and multi-objective particle swarm optimization (MO-PSO) with amplitude and spacing controls are implemented and the results are compared. Better results are obtained by optimizing both excitation amplitudes and spacing between elements in an array, thus the name concurrent optimization.

Keywords
Genetic algorithm, Half-power beam width, Multi-objective optimization, Particle swarm optimization, Side-lobe level.

1.Introduction
The escalating demand for high performance in wireless communication systems has led to the replacement of single antennas with antenna arrays for transmission or reception. An antenna array is typically a group of two or more similar antennas, which function as a single antenna. Due to this, antenna arrays offer higher gain, directivity, signal to noise ratio (SNR), agility and low side lobe level (SLL) [1]. SLL resembles the peak level of minor lobe compared to the main lobe level. It forms one of the key parameters in measurement of antenna array performance. Side lobes usually occur in the direction other than the desired beam direction, making it unwanted and creating interference. Lower the SLL, lower the power wastage and lower the interference with other radiating elements [2]. This increases the efficiency of antenna array.

Lowering the SLL has thus become a prime target for antenna array designers, specifically in technologies like fifth-generation mobile systems, to achieve higher spectral efficiency and signal-to-interference ratio [3]. Among the different techniques aimed at SLL reduction, excitation control is the most common technique, in which the elemental excitations to the antenna array are chosen to achieve the output pattern with desired side-lobe levels. Simple excitation tapering techniques such as Chebyshev and Taylor amplitude distributions reduce the SLL considerably but are not very effective as they require large array size for a desired radiation

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pattern [4]. Evolutionary algorithms are better suited for these applications. Genetic algorithm (GA) is one such dynamic evolutionary algorithm used to solve complicated problems [5]. GA with excitation amplitude control synthesizes the weights of the array to achieve a desired SLL.

One drawback of tapering the elemental excitations is to increase in the width of main lobe [6]. To mitigate this effect, another technique can be used in which the spacing between antenna elements is varied using GA, i.e., non-uniform spacing. In this technique, the excitation amplitude is kept constant. These two techniques can significantly reduce the SLL.

SLL and beam width are usually conflicting in nature, i.e., a reduction in SLL increases the beam width and vice versa, which is undesirable for latest technologies like 5G. The main objective of the work is to reduce side-lobe level of a linear antenna array (LAA), without compromising on the beam width. To simultaneously reduce SLL and beam width, multi-objective optimization algorithms such as genetic algorithm (MO-GA) and particle swarm optimization (MO-PSO) are implemented with amplitude, spacing and concurrent amplitude-spacing controls.

The first section of the paper gives a detailed introduction to the work done. Section 2 discusses about various related papers and their contribution. Section 3 explains the method of approach which includes the antenna array design, algorithms used and fitness function formulation. The sections 4 and 5 present the results of the work and comparison between discussed techniques respectively. Finally, conclusions are stated in section 6.

2.Literature review

Several techniques have been proposed in literature to reduce the side-lobe level. Chebyshev amplitude distribution is implemented in [7] and is compared with particle swarm optimization (PSO). Windowing techniques like Taylor, Kaiser, Hamming, Blackman and Hann were used in [8] and [9]. Chebyshev distribution is not suitable for larger arrays, whereas the Blackman distribution yields wider main beam. To yield the desired radiation pattern and SLL, without much compromise on beam width, an optimum set of excitations or spacing are to be generated by a number of iterations using some specific algorithms.

Several algorithms have been well-defined in previous works, which include PSO, GA, biogeography based optimization (BBO), invasive weed optimization (IWO), bat flower pollination (BFP), etc. [10–14]. In [10], Taylor distribution and classical PSO are used to obtain desired SLL. Implements IWO to optimize elemental excitation amplitudes and phases for reducing SLL and positioning nulls in desired direction [11]. BBO algorithm achieved good SLL reduction and placement of nulls in desired direction by optimizing excitation amplitudes in [12]. In [13], GA is used to find optimum antenna weights that result in maximum reduction in SLL. Implements BFP algorithm, which is the combination of bat algorithm and flower pollination algorithm [14]. It suppressed SLL by optimizing excitations to array elements.

Some recent works include improved chicken swarm optimization (ICSO) [15] for reducing peak SLL, modified sparrow search algorithm (MSSA) [16] using amplitude and spacing control to reduce maximum SLL and improved cuckoo search with reverse learning and invasive weed operators [17] to obtain minimum SLL possible by optimizing element excitations in LAAs. In [18], a salp swarm algorithm (SSA) is proposed to reduce SLL in linear and planar sparse antenna arrays. A moth flame optimization (MFO) is implemented in [19] to lower the SLL in LAA and circular antenna array (CAA) by controlling inter-element spacing and elemental excitations. A hybrid optimization method which combines gray wolf optimization (GWO) and PSO is implemented in [20] to suppress SLL in LAA and CAA with specific radiation characteristics.

All the above algorithms are based on elemental excitation amplitude, phase or spacing controls. Spacing control can yield better results in terms of reduced SLL without increasing beam width significantly. As a first objective of the work, elemental excitations and spacing are varied individually for 16- and 64-element arrays, and their optimum values are obtained for SLL reduction.

Some of the radiation pattern characteristics are conflicting in nature, i.e., an improvement in one characteristic degrades the other. To simultaneously improve the conflicting characteristics, a multi-objective optimization of antenna array parameters is to be implemented. Significant work is also carried out in this area [21–32]. In [21], two design objectives-SLL and null control in specified directions are minimized simultaneously by controlling spacing between array elements using differential evolution. One more conflicting pair – fixed interference suppression and avoiding further rise of SLL, while scanning the beam, are simultaneously achieved by using GA in [22]. Collective social behavior (CSB) algorithm is developed in [23] to minimize SLL and achieve adaptive nulling using antenna weight controls. A backtracking search optimization algorithm (BSA) is implemented in [24] to reduce the maximum SLL with nulls in desired directions. Presents a cuckoo optimization algorithm (COA) aimed at reducing SLL and controlling nulls in LAAs and CAAs [25]. In [26], LAA is designed for reduced SLL and null control using flower pollination algorithm (FPA), by amplitude or spacing control of array elements. A new approach called dynamic cooperative grey wolf optimizer is used to reduce SLL and generate deep nulls at desired positions simultaneously using weighted sum in [27]. In [28], a multi-objective beam pattern optimization problem of reduction of SLL and achieving desired nulls is solved using improved evolutionary algorithm based on decomposition approach. Presents modified version of seagull optimization algorithm (SOA), based on moving and attacking behavior of the seagull, to reduce SLL and control the nulls in LAA pattern [29].

One more optimization method based on mayfly algorithm (MA) is proposed for equally spaced and unequally spaced LAAs in [30] to reduce SLL and increase the null depth. However, the computational time and number of parameters involved are larger. In [31], a brainstorm optimization (BSO) algorithm has been proposed for LAA thinning, to reduce SLL and directivity/SLL ratio. A hybrid GA-PSO based optimization algorithm has been proposed in [32] to reduce SLL and generate deep nulls. 5G technology requires non-interfering, highly directional beams for communication, which implies that the beam width and SLL should be as minimum as possible. But they are conflicting parameters and simple optimization cannot simultaneously reduce both of them. As the second objective of the work, a pareto optimization of SLL and half-power beam width (HPBW) is implemented using MO-GA and MO-PSO using amplitude, spacing and amplitude-spacing controls. The output is a set of non-dominant solutions called pareto front. Any particular point on the pareto front is a valid solution to the problem.

3.Method

Initially, a 16-element uniform linear array of isotropic elements is considered as shown in *Figure 1*. The radiation pattern in θ direction is equal to the array factor in that direction, given by (Equation 1):

$$AF(\theta) = \sum_{n=1}^{N} A(n)\exp\left[j\frac{2\pi}{\lambda}d(n)\cos\theta\right] \quad (1)$$

Where A(n) is excitation amplitude and d(n) are spacing from origin respectively of n^{th} element of the array. λ is wavelength corresponding to the operating frequency and N is the total number of elements of the array. A fixed element spacing d= λ/2 and unity excitation amplitude are considered for the elements. Thus $d(n) = n * d$. The array is simulated using MATLAB2018b and from the resulting radiation pattern, peak level of side-lobe and HPBW values are obtained. Similar procedure is repeated for N=64 and its peak SLL and HPBW are also calculated.

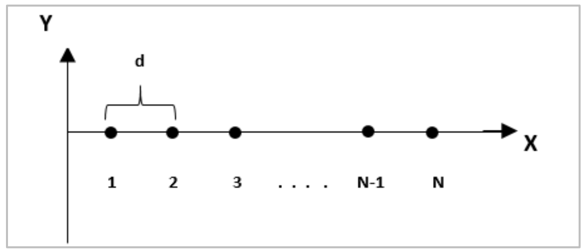

Figure 1 Array geometry

To reduce SLL, the elemental excitations, A(n) are varied between 0 and 1 with the elemental spacing constant at 0.5λ. This approach widens the main beam resulting in reduced directivity. Next, the spacing between elements, d(n) are varied between 0.2λ and 0.8λ, keeping all the elemental excitation values as unity. The maximum value of spacing is taken as 0.8λ to avoid grating lobes. Spacing optimization is found to reduce SLL without widening the main beam much. After performing multiple iterations of GA, optimum values of A(n) and d(n) are obtained. These two techniques are performed for N=16 and 64 and the SLL and HPBW are calculated and compared. In order to reduce the HPBW and SLL, a multi-objective optimization is implemented using GA and PSO. First an amplitude-only control technique is employed and then spacing-only control technique is used. To obtain much lower HPBW for the given SLL, concurrent amplitude-spacing control technique is implemented in this work, in which both excitation amplitudes and spacing are simultaneously optimized. The results of these techniques are a pareto front plot with SLL versus HPBW. This pareto optimization yields a number of solutions instead of a single solution. Most feasible solution can be selected among them.

3.1Genetic algorithm
GA is used for finding optimal solutions to search and optimization problems, based on natural selection and evolutionary genetics. It solves both constrained and unconstrained problems. Similar to biological evolution, GA uses selection to obtain the fittest individuals among a population. These are crossed over and mutated to produce new improved offspring. These new offspring are declared fit for further reproduction using a fitness function, which depends on the problem. The steps selection, crossover and mutation are implemented multiple times until the optimum solutions are reached or a stopping criterion is met [33].

The steps of GA are given below.
Step-1: Creation of random population.
Step-2: Evaluation of Fitness for the population.
Step-3: If stopping criterion is met, go to step-7, else go to step-4
Step-4: Selection of individuals with best fitness.
Step-5: Crossover and mutation applied to the selected individuals to generate new offspring.
Step-6: Go to step 2.
Step-7: End.

3.2Particle swarm optimization
The population in PSO is referred to as swarm and the solutions are referred to as particles. The particles move in search space and the movement is guided by individual best-known positions and the swarm's best-known position. The positions are evaluated based on the fitness function [34]. Along with the position, particle velocity is also updated. After a number of iterations, the best position or solution can be reached.
The steps of PSO are given below.
Step-1: Creation of random population containing n particles.
Step-2: Assign initial velocity and position to each particle.
Step-3: Evaluate fitness of each particle.
Step-4: Update local (of individual) and global (of swarm) best fitness values.
Step-5: Update particle positions and velocities.
Step-6: If stopping criterion is reached, go to step-7, else go to step-3.
Step-7: The optimum solution is in global best.
Step-8: End.

3.3Fitness functions
For minimizing SLL and beam width, the two fitness functions, Fitness1 and Fitness2, described by Equations 2 and 3 respectively, have to be minimized.

$$\text{Fitness1}=SLL_{obtained} - SLL_{des} = \max\left\{20log\left|\frac{AF(\theta)}{AF(\theta)_{max}}\right|\right\} - SLL_{des} \quad (2)$$

$$\text{Fitness2} = \text{HPBW} = 2|\theta_m - \theta_h| \quad (3)$$

Where AF(θ) are array factor values in all directions excluding the main lobe, $AF(\theta)_{max}$ is the maximum or peak value of main lobe, SLL_{des} is the desired value of SLL which is taken as -30 decibels (dB) in this paper, θ_m corresponds to $AF(\theta)_{max}$ and θ_h corresponds to $0.707\times AF(\theta)_{max}$, which is nothing but the half-power level of $AF(\theta)_{max}$. $SLL_{obtained}$ represents the peak side-lobe level obtained, and in Equation (3), θ_m is taken as $\pi/2$ for broad-side array. Fitness1 can be minimized using simple GA or PSO, but at the cost of increment in Fitness2, and vice-versa. Both fitness functions are to be minimized simultaneously, which is not possible using simple optimization technique. Therefore, multi-objective GA and PSO are used to produce a set of solutions called pareto Front. A plot of Fitness1 versus Fitness 2 represents pareto optimization of SLL and HPBW for the LAA. The numerical calculations of $SLL_{obtained}$ and HPBW are as follows: for example, a 16-element uniform LAA with spacing between elements, d=0.5λ and elemental excitations of unity, obtained main lobe peak of amplitude 16 and peak side lobe of amplitude 3.489 as shown in *Figure 2*. θ_m observed is 90^0 and θ_h corresponding to half power is -86.83^0 . Then,
$SLL_{obtained} = 20\log\left(\frac{3.489}{16}\right)$ dB = -13.23 dB and
HPBW = 2 (90^0 - 86.83^0) = 6.34^0 .

4.Results
For a 16-element uniform linear array having spacing between elements d=0.5λ, excited uniformly with unity amplitude, the array factor plot obtained is indicated in *Figure 2* below. From the plot, an SLL of -13.23 dB ($\text{i.e.}\, 20\log\left(\frac{3.489}{16}\right)$ dB) and a HPBW of 6.34^0 (by taking twice the difference of angles at main lobe peak and at 0.707 times the peak) are observed. The SLL can further be reduced by optimizing the amplitude or spacing.

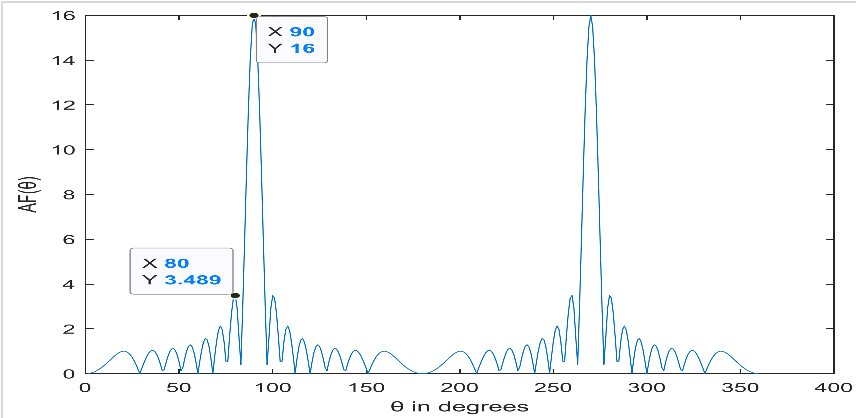

Figure 2 Rectangular plot of Array Factor when unity excitations and λ/2 spacing are applied for 16-element array

The SLL has been considerably reduced using GA optimization with the fitness function given by Fitness1 in equation 2, and the optimization curve is shown in *Figure 3*. The weights of excitation are optimized after 500 iterations and using the optimized excitations, rectangular plot of array factor is obtained as shown in *Figure 4*, from which an SLL of -20.63 dB ($SLL_{obtained}$) and a half power beam width of 7.84^0 are calculated. A decrease in SLL has led to an increase in beam width. Also, a decrease in peak value, $AF(\theta)_{max}$ is observed. This is because of amplitude tapering, which reduces amplitude of excitation of few elements.

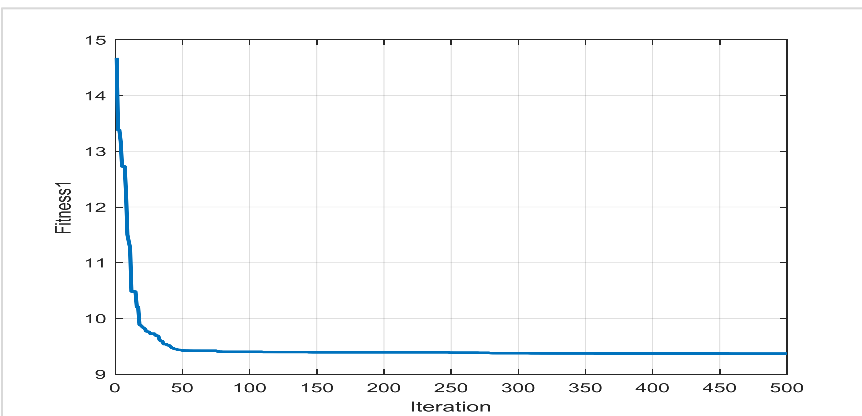

Figure 3 GA optimization curve of Fitness1 function using amplitude control for 500 iterations

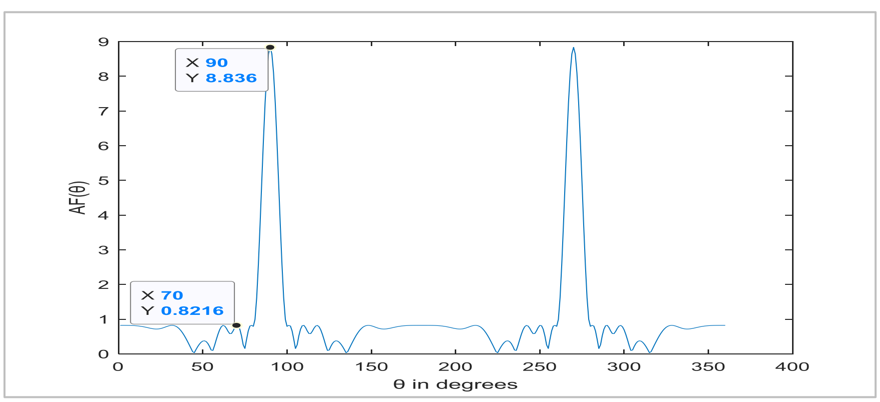

Figure 4 Rectangular plot of array factor when element excitations are GA optimized for SLL reduction

In spacing optimization technique, the factor d/λ is varied between 0.2 and 0.8, and the fitness function is reduced to 9.04dB, as shown in *Figure 5*, when the excitation amplitudes are all unity. Using the optimized spacing values, array factor obtained is as shown in *Figure 6* and the beam width calculated from this plot is 6.72^0 , while the SLL calculated is reduced to -20.95 dB. This is an improvement over amplitude optimization technique. Also, the main lobe level is not reduced, unlike in amplitude optimization case, where the amplitudes vary between 0 and 1. The array size is further increased to N=64 isotropic elements and the array factor plot observed for uniform elemental excitations of unity and an element spacing of 0.5λ is shown in *Figure 7*. An SLL of -15.79 dB and a HPBW of 1.34^0 are calculated from the plot. The increase in number of antenna elements from 16 to 64 has resulted in decrease in HPBW from 6.34^0 to 1.34^0 .

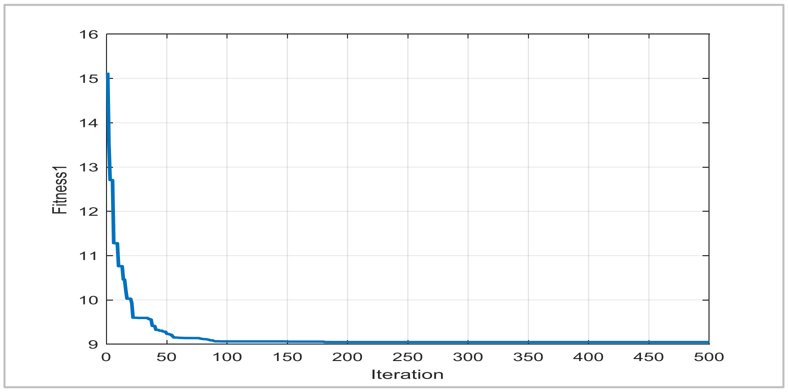

Figure 5 GA optimization curve of Fitness1 function using spacing control for 500 iterations

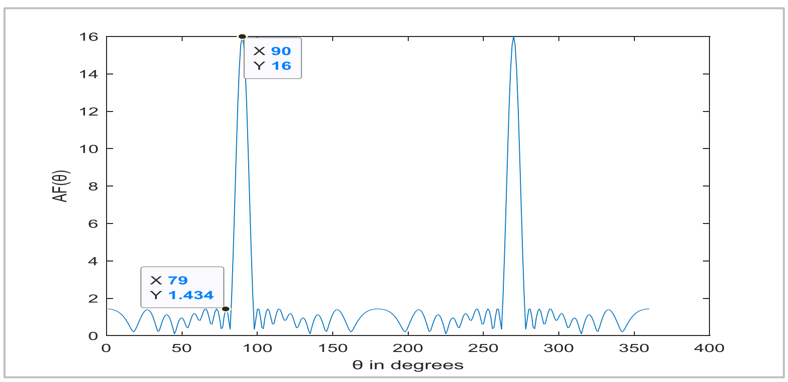

Figure 6 Rectangular plot of Array factor when spacing between elements, d/λ are GA optimized for SLL reduction

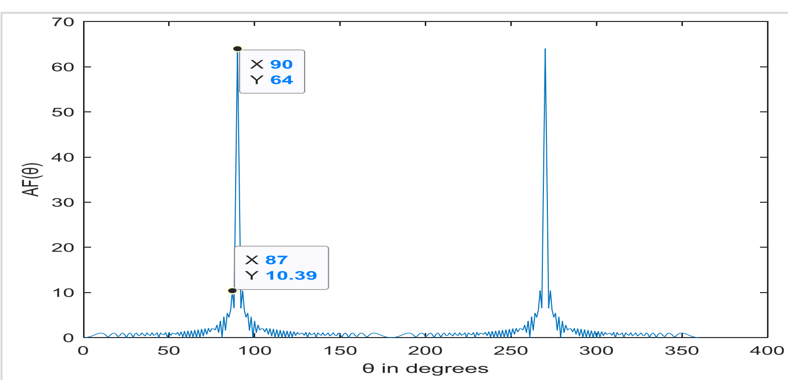

Figure 7 Rectangular plot of Array factor when unity excitations and λ/2 spacing are applied for 64-element array

By applying excitation amplitude optimization on the 64-element array, amplitudes are varied between 0 and 1 keeping uniform element spacing d=0.5λ. The minimum value of fitness function obtained is 7.10 dB after 500 iterations, as seen in *Figure 8*. From *Figure 9*, an SLL of -22.93 dB is observed and HPBW of 1.62^0 is obtained, which is an increment over the HPBW in no optimization case. Reduction in SLL is accompanied by increase in HPBW in amplitude optimization case.

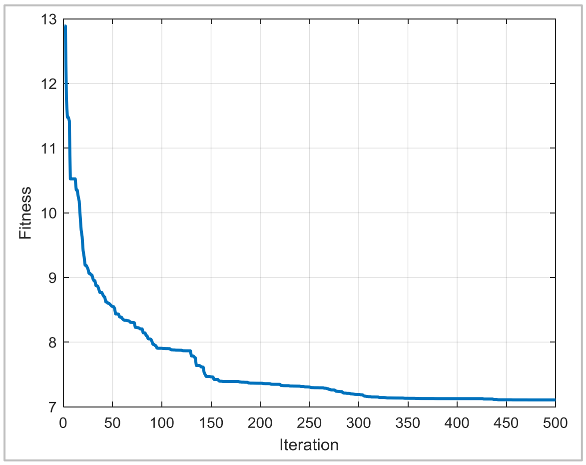

Figure 8 GA amplitude optimization curve for fitness function after 500 iterations (N=64)

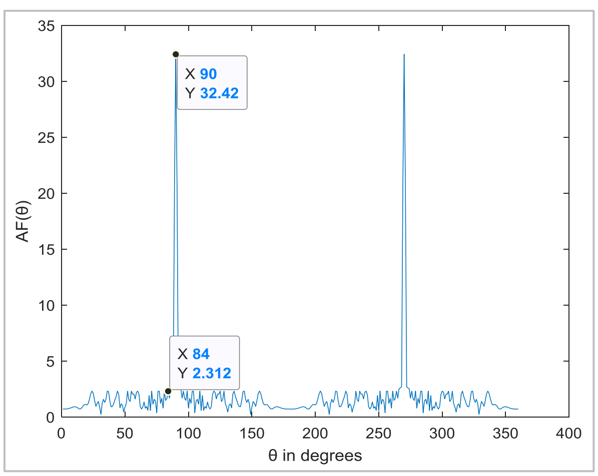

Figure 9 Rectangular plot of array factor when GA optimized excitations and λ/2 spacing are applied for 64-element array

By using spacing optimization technique, the amplitude excitations are maintained unity and spacing between antenna elements is varied between 0.2λ and 0.8λ. The best value of fitness obtained is 4.68 dB after 500 iterations as seen in *Figure 10*. The SLL obtained is -25.31 dB with a HPBW of 1.12^0 , as calculated from *Figure 11*. These values are better compared with amplitude optimization and no optimization cases.

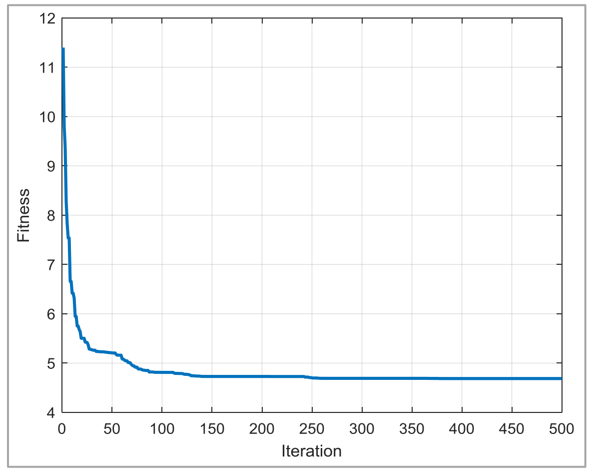

Figure 10 GA spacing optimization curve for fitness function after 500 iterations (N=64)

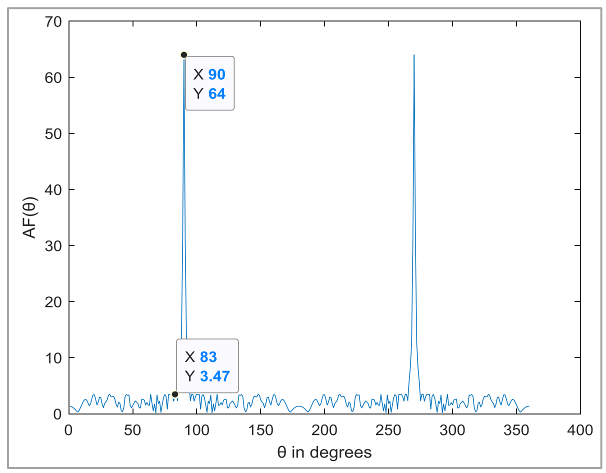

Figure 11 Rectangular plot of array factor when unity excitations and GA optimized spacing are applied for 64-element array

To reduce both SLL and beamwidth, multi-objective GA using Amplitude-only control is employed. The spacing is maintained at d = 0.5λ and amplitudes are varied between 0 and 1. The pareto optimized output is a set of 70 non-dominant solutions as shown in *Figure 12*. The point P1 in *Figure 12* shows an SLL of -20.7 dB, which is obtained from Equation 2 when SLL is chosen as -30dB, and a HPBW of 6.94^0 . This is an improvement over the side-lobe level of -20.63dB and a half power beamwidth of 7.84^0 in simple GA using amplitude control (*Figure 4*), since HPBW is reduced for nearly equal SLL. The point P2 shows an SLL of -16.4 dB (i.e., -30 dB + 13.591 dB) and a HPBW of 6.34^0 . This is an improvement over an SLL of -13.23dB and a HPBW of 6.34^0 (*Figure 2*) of un-optimized uniform linear array, since, the SLL is reduced for the same value of HPBW. This implies that MO-GA with amplitude-only control performs better than no-optimization case and simple GA with amplitude-only control case.

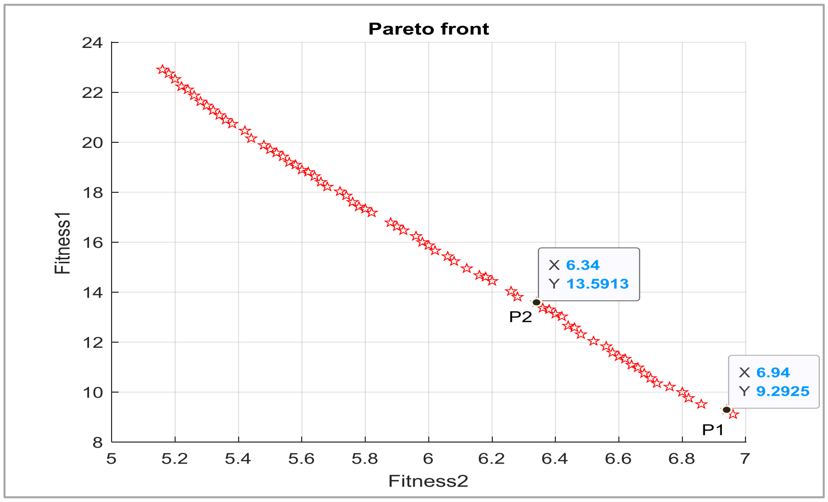

Figure 12 Pareto front obtained for Fitness1 ($SLL_{obtained}$-SLL_{des}) versus Fitness2 (HPBW) using amplitude-only control in MO-GA

Next, the pareto optimization is implemented using spacing-only control. The excitation amplitudes are maintained unity while the spacing between elements, $d\,/\,\lambda$ is varied between 0.2 and 0.8. For first element, distance from origin is considered. The pareto optimization is represented by a set of 70 solutions as shown in *Figure 13*. The point P3 shows SLL of -20.61 dB (i.e., -30 dB + 9.385 dB) and a HPBW of 6.1^0 . This is an improvement over SLL of -20.95 dB and HPBW of 6.72^0 of simple GA using spacing optimization in *Figure 6*, in terms of reduced HPBW for nearly equal SLL. Similarly, P3 is better compared to P1 (SLL of -20.7 dB and HPBW of 6.94^0) in *Figure 12*, making spacing-control better than amplitude-control for reducing SLL and HPBW.

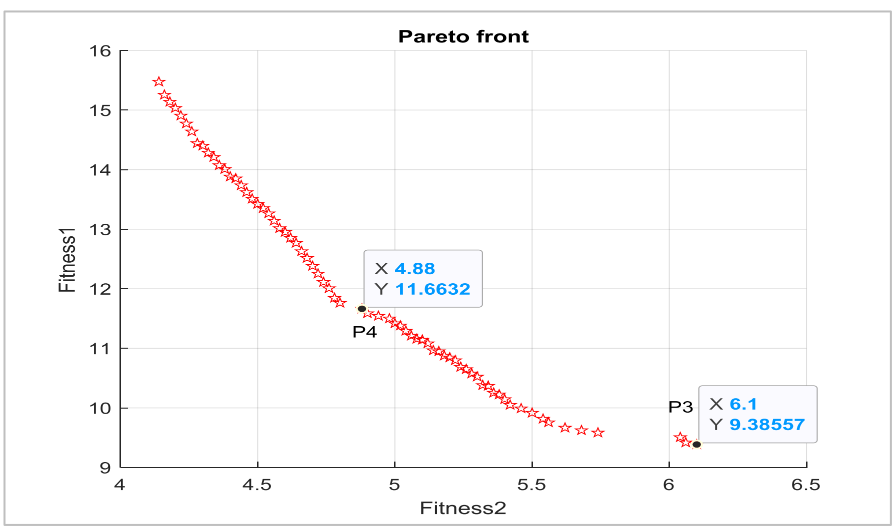

Figure 13 Pareto front obtained for Fitness1 (〖SLL〗 _obtained- 〖SLL〗 _des) versus Fitness2 (HPBW) using spacing-only control in MO-GA

Further, the pareto optimization is implemented with concurrent amplitude-spacing control. The excitation amplitudes are varied between 0 and 1, and the spacing between elements, d / λ is varied between 0.2 and 0.8. The obtained solution set contains 64 points as shown in *Figure 14.* The point P5 indicates an SLL of -20.71 dB (i.e., -30 dB + 9.285 dB) and a HPBW of 4.6^0 , which is clearly better than P3 and P1, in terms of reduced beamwidth for nearly equal SLL. If further reduction in SLL is preferred, the solution can be moved to P6, which shows an SLL of -22.89 dB (i.e., -30 dB + 7.11 dB) and HPBW of 5.38^0 .

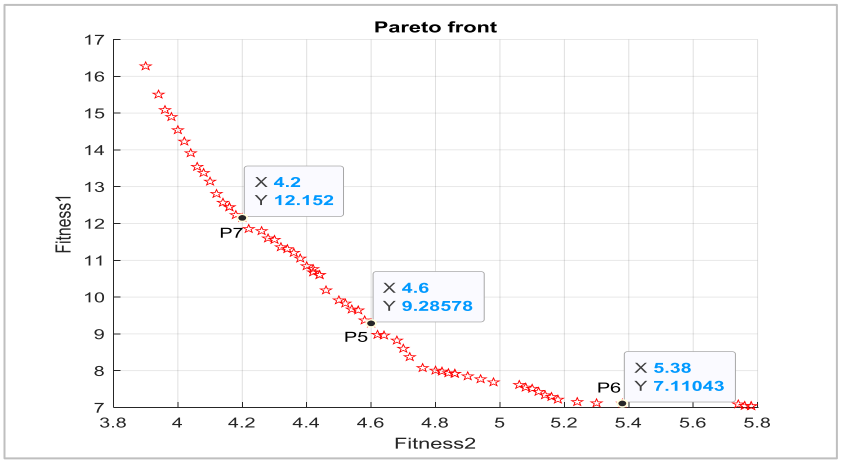

Figure 14 Pareto Front obtained for Fitness1 ($SLL_{obtained}$-SLL_{des}) versus Fitness2 (HPBW) using concurrent amplitude-spacing control in MO-GA

MO-PSO is also implemented with amplitude-only control, i.e., the spacing is maintained at d = 0.5λ and amplitudes are varied between 0 and 1. The pareto front is a set of 69 solutions and the point P8 indicates an SLL of -20.46 dB (i.e., -30 dB + 9.536 dB from eq. 2) for a beamwidth of 7.14^0 as shown in *Figure 15*. This is not a better performance in comparison with amplitude-only control MO-GA (P1 with SLL of -20.7 dB and HPBW of 6.94^0 in *Figure 12*), but is still a good trade-off.

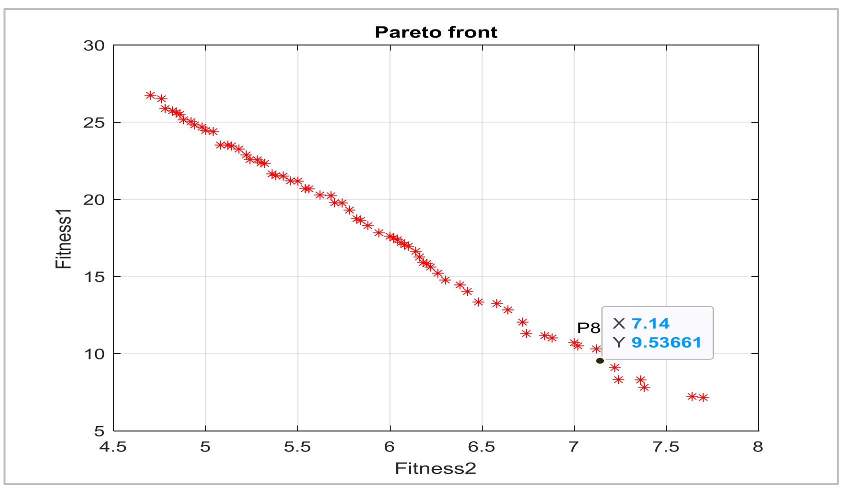

Figure 15 Pareto front obtained for Fitness1 (〖SLL〗 _obtained- 〖SLL〗 _des) versus Fitness2 (HPBW) using amplitude-only control in MO-PSO

Next, PSO is implemented with spacing-only control, i.e., the excitation amplitudes are maintained unity while the spacing between elements, d / λ is varied between 0.2 and 0.8. For first element, distance from origin is considered. The set of 35 output pareto solutions are shown in *Figure 16*. The point P9 indicates an SLL of -18.33 dB (i.e., -30 dB + 11.661 dB from eq. 2) for a beamwidth of 4.94^0 . This is comparable to point P4 of spacing-only control MO-GA in *Figure 13* (SLL of -18.33 dB with a HPBW of 4.88^0). Finally, MO-PSO with concurrent amplitude and spacing control is implemented, i.e., the excitation amplitudes are varied between 0 and 1, and the spacing between elements, $d\ /\lambda$ is varied between 0.2 and 0.8. The obtained pareto front of 34 solutions is shown in *Figure 17*. Point P10 indicates an SLL of -17.89 dB (i.e., -30 dB + 12.11 dB) and HPBW of 4.2^0 . This is comparable to point P7 (SLL of -17.84 dB and HPBW of 4.2^0) of amplitude-spacing control MO-GA.

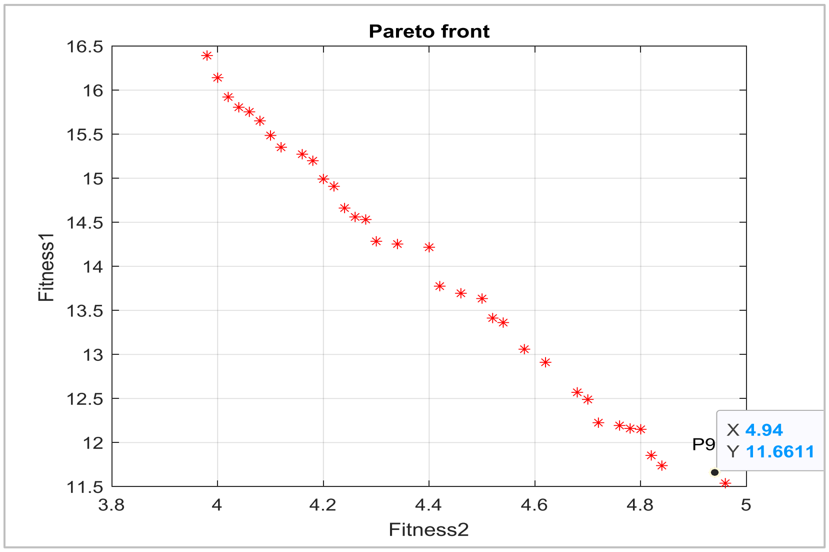

Figure 16 Pareto Front obtained for Fitness1 (〖SLL〗 _obtained- 〖SLL〗 _des) versus Fitness2 (HPBW) using spacing-only control in MO-PSO

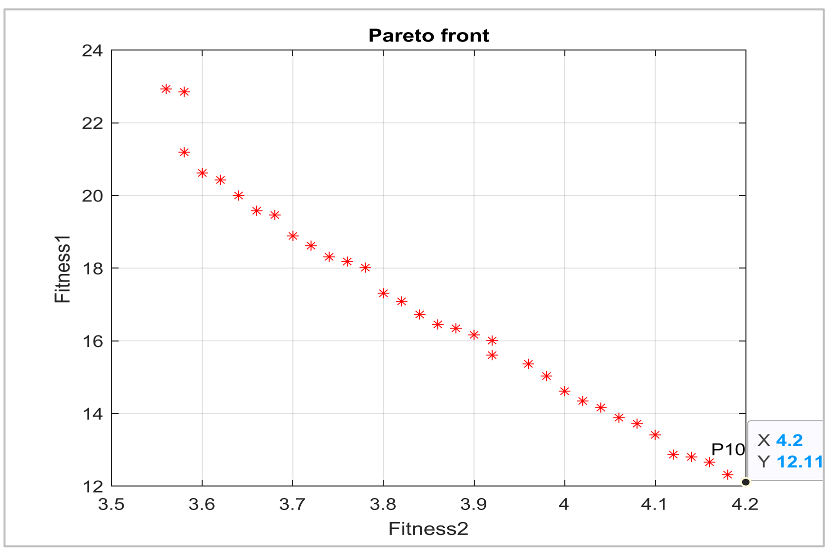

Figure 17 Pareto Front obtained for Fitness1 ($SLL_{obtained}$-SLL_{des}) versus Fitness2 (HPBW) using concurrent amplitude-spacing control in MO-PSO

5.Discussion

A comparison of SLL and HPBW obtained using amplitude and spacing optimization in GA. It is indicated in *Table 1* for 16-element and 64-element LAAs.

Table 1 A comparison of amplitude and spacing optimization techniques for N=16 and 64

N.	No. optimization		Amplitude optimization		Spacing optimization	
	SLL	HPBW	SLL	HPBW	SLL	HPBW
16	-13.23 dB	6.34^0	-20.63 dB	7.84^0	-20.95 dB	6.72^0
64	-15.79 dB	1.34^0	-22.93 dB	1.62^0	-25.31 dB	1.12^0

From the table, the following points can be inferred:

- It is seen that as the antenna array size increases, the beam width gets narrower and also the SLL reduces to some extent. This reduction in peak SLL can be attributed to increase in number of sidelobes with N.
- Amplitude optimization reduces the SLL and a further reduction in SLL can be achieved through spacing optimization.
- The HPBW in spacing control technique is also lower compared to that of amplitude optimization technique.
- For N=64, spacing optimization technique showed a reduction in SLL by 9.52 dB and 2.38 dB compared with no optimization and amplitude optimization cases respectively. The beamwidth is also lowest for spacing optimization case.
- Since beamwidth and directivity are inversely proportional, the 64-element antenna array with spacing optimization has the best directivity among others discussed above.

A comparison of SLL and HPBW for different single and multi-objective optimization techniques using amplitude-only, spacing-only and amplitude-spacing controls is presented in *Table 2.* Note that the array size considered is 16.

Table 2 Comparison of results of various techniques discussed above

Optimization technique	SLL *(in dB)*	HPBW *(in degrees)*
No optimization	-13.23 dB	6.34^0
GA (Amplitude control)	-20.63 dB	7.84^0
GA (Spacing control)	-20.95 dB	6.72^0
MO-GA (Amplitude control)	-20.7 dB (P1)	6.94^0
MO-GA (Spacing control)	-20.61 dB (P3)	6.1^0
MO-GA (Concurrent Amplitude-Spacing control)	-20.71 dB (P5)	4.6^0
MO-PSO (Amplitude control)	-20.46 dB (P8)	7.14^0
MO-PSO (Spacing control)	-18.33 dB (P9)	4.94^0
MO-PSO (Concurrent Amplitude-Spacing control)	-17.89 dB (P10)	4.2^0

From the table, the following points can be inferred:

- MO-GA and MO-PSO are found to achieve much lower beamwidths compared to GA, for nearly equal SLL values.
- Concurrent amplitude and spacing control optimization have resulted in lower beamwidth, making it more superior over amplitude-only and spacing-only controls.

Multi-objective optimization techniques have facilitated the simultaneous reduction of both SLL and beamwidth, which is desired in most of the upcoming communication technologies. MO-GA and MO-PSO have performed almost equally in reducing beamwidth for a given SLL. However, the implementation of concurrent amplitude and spacing controls in this work have drastically improved the results.

5.1Limitation

Practically, the excitation amplitude control requires specialized feed network designed to generate required excitation for each element of the array. Thus, concurrent amplitude-spacing control technique requires complex hardware. A complete list of abbreviations is shown in *Appendix I.*

6.Conclusion and future work

The SLL for a 16-element array is reduced by excitation amplitude optimization using GA. As a consequence, the HPBW is increased. While in spacing optimization, SLL and HPBW are reduced compared to excitation optimization, which improves the array antenna performance. In a 64-element array, the beamwidth is very less compared to that of 16-element array, making the beam more focused. In this case also, spacing optimization has less SLL and HPBW than amplitude optimization. Thus, array antennas with optimized spacing perform better than those with optimized excitation amplitudes for different antenna sizes. Also, amplitude control MO-GA and MO-PSO exhibit better performance than simple GA with amplitude control. But spacing control MO-GA and MO-PSO perform better than amplitude control MO-GA and MO-PSO in terms of reduced HPBW. Concurrent amplitude-spacing control MO-GA and MO-PSO show the best performance among all other techniques discussed above, by exhibiting the least HPBW for a given SLL. Also, the performance of MO-GA is comparable to that of MO-PSO, with MO-GA slightly better than MO-PSO in few cases in terms of number of solutions.

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Conflicts of interest
The authors have no conflicts of interest to declare.

Author's contribution statement
Y. Laxmi Lavanya: Conceptualization, investigation, writing – original draft, writing-review and editing-data collection, conceptualization, writing-original draft, analysis and interpretation of results. **G. Sasibhushana Rao:** Study conception, design, data collection, supervision, investigation on challenges and draft manuscript preparation.

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Appendix I

S. No.	Abbreviation	Description
1	5G	Fifth Generation Mobile Network
2	BBO	Biogeography Based Optimization
3	BFP	Bat Flower Pollination
4	BSA	Backtracking Search Optimization Algorithm
5	BSO	Brainstorm Optimization
6	CAA	Circular Antenna Array
7	CSB	Collective Social Behavior
8	COA	Cuckoo Optimization Algorithm
9	dB	Decibels
10	FPA	Flower Pollination Algorithm

11	GA	Genetic Algorithm
12	GWO	Gray Wolf Optimization
13	HPBW	Half Power Beam Width
14	ICSO	Improved Chicken Swarm Optimization
15	IWO	Invasive Weed Optimization
16	LAA	Linear Antenna Array
17	MA	Mayfly Algorithm
18	MFO	Moth Flame Optimization
19	MO-GA	Multi-Objective Genetic Algorithm
20	MO-PSO	Multi-Objective Particle Swarm Optimization
21	MSSA	Modified Sparrow Search Algorithm
22	PSO	Particle Swarm Optimization
23	SLL	Side Lobe Level
24	SNR	Signal to noise ratio
25	SOA	Seagull Optimization Algorithm
26	SSA	Salp Swarm Algorithm