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Design of Linear and Circular Antenna Array for Side Lobe Reduction Using the Method Moth Flame Optimization Algorithm

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ABSTRACT

A design problem of symmetrical linear antenna array (LAA) and a non-uniformly excited single ring circular antenna array (CAA) for minimized side lobe level (SLL) is presented in this paper .Moth Flame optimization (MFO) is considered one of the promising meta heuristic algorithms and successfully applied in various optimization problems .In this paper, MFO is applied to determine inter-element spacing and current excitation weights among the elements to reduce SLL and improve the half power beam width (HPBW) and improve first null beam width (FNBW). The simulation results of the designed LAA, CAA are compared with a fully populated array to illustrate the effectiveness of our proposed method.

KEYWORDS: linear antenna array, side lobe level, circular antenna array, moth flame optimization, half power beam width.

1. INTRODUCTION

A group of antenna elements which are excited to achieve a desired radiation pattern in a given direction is called Antenna array. They can provide capability of beam steering. Antenna arrays are widely used in sonar, radar, communication and high power transmission applications. The radiation pattern depends on the antenna array parameters like geometrical configuration of the array, inter-element spacing and the current excitation weights of each array element. Array antennas have a high gain and directivity compared to an individual radiating element. The goal in antenna array geometry synthesis is to determine the physical layout of the array that produces the radiation pattern that is close to the desired pattern (Ballanis CA.1997, Elliott RS.2003). The increasing pollution of electromagnetic environment prompts to design the antenna array with lower side lobe level (SLL) and narrower half power beam width (HPBW).

In this paper presents an accurate approach to design a symmetrical linear antenna array (LAA) and a non-uniformly excited single ring circular antenna array (CAA) to improve the far-field radiation characteristics. The LAA and CAA synthesis can be achieved either by optimizing the inter-element spacing keeping a uniform current excitation weight and phase or optimizing the current and phase excitation weights while maintaining a uniform inter-element spacing.

The far-field radiation pattern is improved with SLL which is essential for the reduction of interference in the entire side lobe regions. The current excitation weights and the inter-element spacings are optimized in this paper by using MFO algorithm for the synthesis of LAA keeping the inter-spacing as d=λ/2 and phase excitation weights as zero for 10-element, 12-element, 18-element symmetrical LAA design. The current excitation weights and the inter-element spacing are optimized in this paper by using MFO algorithm for synthesis of non- uniform CAA for 10-element, 12-element, and 16-element non-uniform CAA design.

In this paper, the design constraints of narrower FNBW, lower SLL and narrower HPBW for symmetrical LAA and non-uniform CAA design have been considered by using MFO algorithm. The constraints are as follows: to improve the directivity of the radiation pattern by reducing the value of HPBW, to reduce side lobe levels, in the radiation pattern imposing nulls at all the peak of side lobes. The primary objective of this paper is to design non-uniform CAA and a symmetrical LAA with the lowest SLL value while maintaining a narrow HPBW by using MFO algorithm. MFO was initially proposed by S.Mirjalili. MFO is a meta-heuristic algorithm inspired by the behavior of moths converging towards the light. The current excitation amplitude weights of each array element and the inter-element spacing are optically calculated by using MFO, and the best results are presented.

2. DESIGN EQUATION

2.1 Linear antenna array (LCC)

Linear antenna array is array that consists of number of elements in a straight line. An isotropic array elements of even number, 2M is considered and positioned symmetrically along the z-axis (Khodier M, Al- Aqeel M.2009). The separation between the array elements is d=λ/2, M elements are placed on each side of the origin.

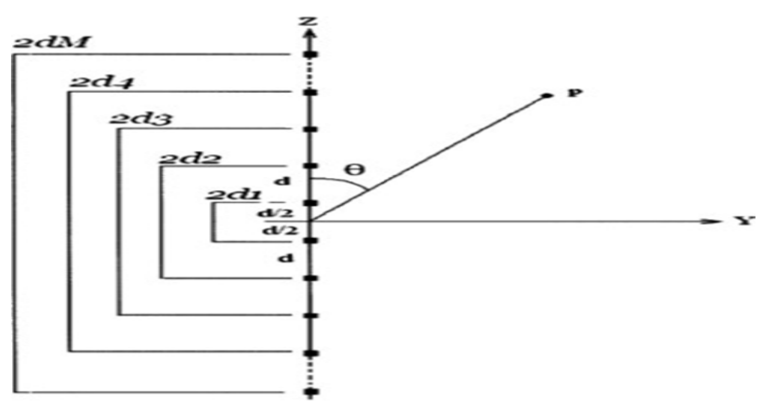

FIGURE 1: 2M-elements linear antenna array geometry along the Z axis

Assuming that the amplitude excitation is symmetrical about the origin and the array factor (AF) of the non-uniform amplitude broadside array is given by Equation (1).

$$(AF)_{2M}=2\sum_{n=1}^{M} I_n \cos[((2n-1)/2).k.d.\cos\theta+\Phi n] \quad (1)$$

Where In = current excitation amplitude weight of an nth element, 2 M = total number of elements in the array; k = propagation constant; φn = phase excitation weight of nth element and is considered to be zero for the design to keep the main beam fixed; d = spacing between the array elements, θ = angle of radiation of electromagnetic plane wave.

2.2 Circular antenna array (CAA)

A non uniform circular antenna array is an array that consists of single circle and number of elements on its surface with same centre, having different current excitation amplitude. Consider a non-uniformly spaced N elements CAA lying on the x-y plane, scanning at point PP in the far field and having radius "a" which is shown in Figure 2.

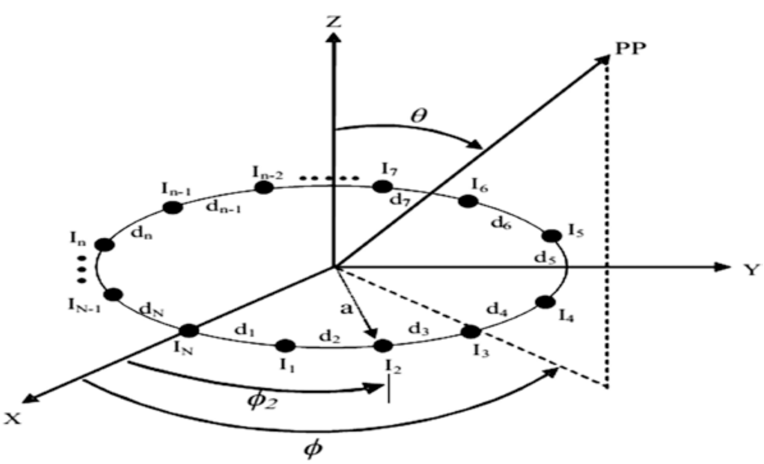

FIGURE 2 : The geometry of N-elements non-uniform CAA laid on the x-y plane for scanning at a point "PP" in the far field

In CAA, each element is assumed to be isotropic source and Array Factor (AF) of non-uniform CAA is given (Elliott RS.2003) by Equation (2).

$$AF(\theta, \Phi, I) = \sum_{n=1}^{N} I_n \exp(j[ka\sin\theta\cos(\Phi-\Phi_n)+\alpha_n]) \quad (2)$$

Where

$$ka = 2\prod a/\lambda = \sum_{i=1}^{N} d_i/\lambda = N \quad (3)$$

$$\Phi_n = 2\prod (n/N) \quad (4)$$

where I_n is the current excitation of n^{th} element of the array, $k = 2\pi/\lambda$; λ is the wavelength of operation; d_i is the inter- element spacing between the elements "i" and "$i+1$," θ is the elevation angle measured from positive z-axis, ϕ is the azimuth angle measured from the positive x-axis, and ϕ_n is the angular location of the n^{th} element along the x-y plane.α_n is the phase excitation of the n^{th} element. N is the total number of elements present in the CAA.

The AF value of Equation (2) attains maximum when

$$ka \sin\theta \cos(\Phi - \Phi_n) + \alpha_n = 2m\pi; \quad \text{where m} = 0, \pm1, \pm2, \ldots \pm n. \qquad (5)$$

The principal maxima are defined by the direction $(\theta_0, \varphi_0)$for which

$$\alpha_n = -ka \sin\theta \cos(\Phi - \Phi_n); \quad n=1,2,\ldots\ldots N. \qquad (6)$$

To direct the peak of the main beam in the (θ_0, ϕ_0) direction, the following changes are assumed for the present design.

$$\theta = \prod/2, \Phi_0 = 0 \text{and } \alpha_n = -ka\cos(\Phi - \Phi_n) \qquad (7)$$

Thus, Equation (2) can be rewritten as

$$AF(\theta,\Phi,I) = \sum_{n=1}^{N} I_n \exp(jka[\cos(\Phi - \Phi_n) - \cos(\Phi_0 - \Phi_n)]) \qquad (8)$$

3. COST FUNCTION FORMULATION

To achieve the design goal, a suitable Cost Function (CF) needs to be formulated for reducing the SLL and HPBW and it is given by equation (9).

$$CF = W_1 X \frac{|AF(\theta_{ms1}, I_n) + AF(\theta_{ms2}, I_n)|}{AF(\theta_0, I_n)} + W_2 X \frac{|\prod_{\theta=-\pi}^{\pi} AF(\theta_{SLL_{peaks}}, I_n)|}{|AF_{max}|} + W_3 X [HPBW_{computed} - HPBW(I_n=1)] \qquad (9)$$

W_1, W_2, W_3 are the weighting factors whose values are selected as 18, 18, and 12, respectively, and θ_0 is the value of θ where the crest of the main lobe is attained; θ_{ms1}, θ_{ms2} are the angle of the maximum side lobe in the lower band and upper band respectively. HPBW is the angular separation between the 3-dB points on each side of the main beam. Thus, $HPBW_{Computed}$ and HPBW ($I_n = 1$) refer to the computed 3-dB beam width for the non-uniform excitation and uniform excitation cases, respectively. . These SLL peaks are represented as $AF(\theta_{SLL\_Peaks}, I_n)$ within $\theta \in [-\pi:\theta_{ms1}, \theta_{ms2}:\pi]$, and $|AF_{max}|$ is the maximum value of AF. $\prod$ represents the product of all the values of $AF(\theta_{SLL\_Peaks}, I_n)$. So, the minimization of *CF* refers to the maximum reduction of SLL and reduction of HPBW as far as possible. MFO algorithm controls the current excitation weights and the inter-element spacing among the array elements to minimize the CF given in Equation (9).

4. MOTH FLAME OPTIMIZATION (MFO) ALGORITHM

Moth–flame optimization (MFO) algorithm was proposed by Mirjalili. It is under the population-based metaheuristic algorithms (Mirjalilli S.2015). As shown in flowchart MFO starts by generating moths randomly within the solution space, then calculating the fitness values (i.e., position) of each moth, and tagging the best position by flame. After that, updating the moths' positions depends on a spiral movement function to achieve better positions tagged by a flame, updating the new best individual positions, and repeating the previous processes (i.e., updating the moths' positions and generating new positions) until the termination criteria are met (Khalilpourazari S, Pasandideh SHR.2017).

The language used to explain the MFO follows from analogy of moth in flame. These key terms are

1. **Decision variable** :Moth's position in each dimension
2. **Solutions**: Moth's position
3. **Initial solutions**: Random positions of moths
4. **Current solutions**: Current positions of moths
5. **New solutions**: New positions of moths
6. **Best solutions:** Flame's position
7. **Fitness function:** Distance between moth and flame
8. **Process of generating new solution**: Flying in a spiral path toward a flame

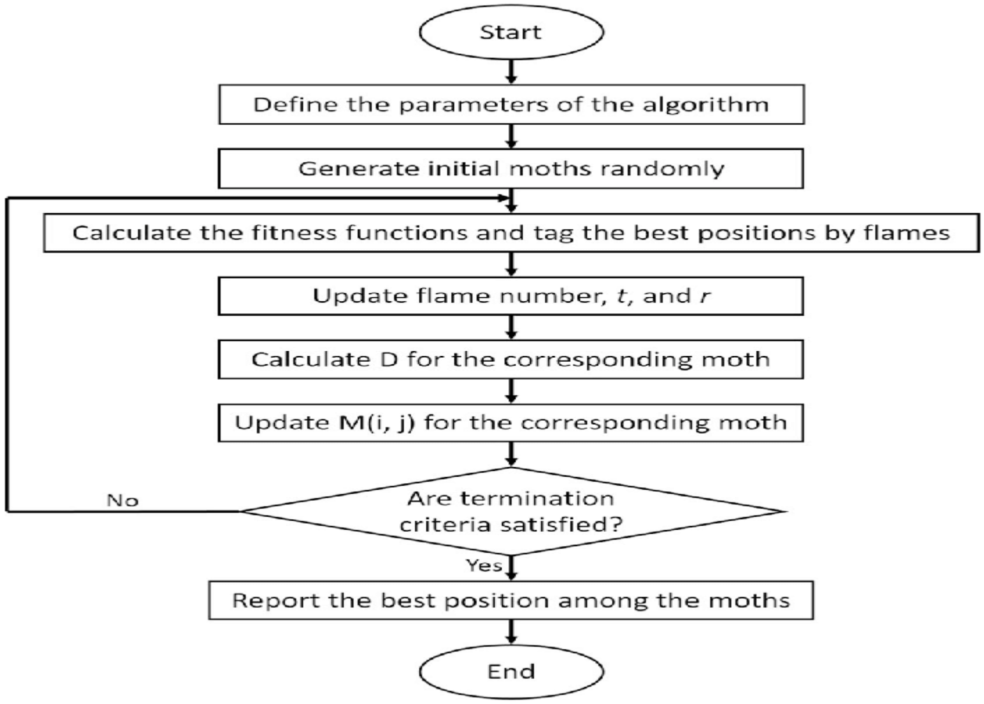

Figure 3: Flowchart of the MFO algorithm

The MFO algorithm has three main steps. These steps are shown below. Then, the pseudocode of the MFO as shown in Algorithm 1 and the summary of its parameters setting are illustrated in Table 2.

1. Generating the initial population of Moths: As mentioned, Mirjalili assumed that each moth can fly in 1-D, 2-D, 3-D, or hyperdimensional space. The set of moths can be expressed in equation 1. where n refers to the moths' number and d refers to the number of dimensions in the solution space

$$M = \begin{bmatrix} m_{1,1} & m_{1,2} & \cdots & \cdots & m_{1,d} \\ m_{2,1} & m_{2,2} & \cdots & \cdots & m_{2,d} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ m_{n,1} & m_{n,2} & \cdots & \cdots & m_{n,d} \end{bmatrix} \quad (10)$$

Also, the fitness values for all moths are memorized in an array as follows:

$$OM = \begin{bmatrix} OM_1 \\ OM_2 \\ \vdots \\ OM_n \end{bmatrix} \quad (11)$$

The rest elements in the MFO algorithm are flames. The following matrix shows the flames in the D-dimensional space followed by their fitness function vector:

$$F = \begin{bmatrix} F_{1,1} & F_{1,2} & \cdots & \cdots & F_{1,d} \\ F_{2,1} & F_{2,2} & \cdots & \cdots & F_{2,d} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ F_{n,1} & F_{n,2} & \cdots & \cdots & F_{n,d} \end{bmatrix} \quad (12)$$

$$OF = \begin{bmatrix} OF_1 \\ OF_2 \\ \vdots \\ OF_n \end{bmatrix} \quad (13)$$

It should be noted here that moths and flames are both solutions. The difference between them is the way we treat and update them in each iteration. The moths are actual search agents that move around the search space, whereas flames are the best position of moths that obtains so far. In other words, flames can be considered as flags or pins that are dropped by moths when searching the search space. Therefore, each moth searches around a flag (flame) and updates it in case of finding a better solution. With this mechanism, a moth never loses its best solution.

2. Updating the Moths' Positions: MFO employs three different functions to converge the global optimal of the optimization problems. These functions are defined as follows:

$$MFO = (I, P, T) \quad (14)$$

where I refers to the first random locations of the moths ($I : \Phi \rightarrow \{M, OM\}$), P refers to motion of the moths in the search space($P : M \rightarrow M$), and T refers to finish the search process ($T : M \rightarrow true, false$). The following equation represents I function, which is used for implementing the random distribution.

$$M(i,j)=(ub(i) - lb(j)) * rand() + lb(i) \quad (15)$$

where lb and ub indicate the lower and upper bounds of variables, respectively. As mentioned previously, the moths fly in the search space using the transverse orientation. There are three conditions that should abide when utilizing a logarithmic spiral subjected, as follows:

– Spiral's initial point should start from the moth.
– Spiral's final point should be the position of the flame.
– Fluctuation of the range of spiral should not exceed the search space.

Therefore, the logarithmic spiral for the MFO algorithm can be defined as follows:

$$S(M_i,F_j) = D_i \cdot e^{bt} \cdot \cos(2\prod t) + F_j \quad (16)$$

where D_i refers to the space between the i-th moth and the j-th flame (i.e., $D_i = |F_j - M_i|$), b indicates a fix to define the shape of the logarithmic spiral, and t indicates a random number between [-1, 1]. In MFO, the balancing between exploitation and exploration is guaranteed by the spiral motion of the moth near the flame in the search space. Also, to avoid falling in the traps of the local optima, the optimal solutions have been kept in each repetition, and the moths fly around the flames (i.e., each moth flies surrounding the nearest flame) using the OF and OM matrices.

3. Updating the number of flames: This section highlights enhancing the exploitation of the MFO algorithm (i.e., Updating the moths' positions in n various locations in the search space may decrease a chance of exploitation of the best promising solutions). Therefore, decreasing the number of flames helps to solve this issue based on the following equation:

PARAMETRS	MFO
Population size	10
T	50
B	1
T	[0,1]
R	[-1,-2]

$$\text{flame no} = \text{round}(N - l * (N - 1)/T) \quad (17)$$

where N is the maximum number of flames, l is the current number of iterations, and T indicates the maximum number of iterations.

The P function is executed until the T function returns true. The main steps of MFO algorithm utilized for the LAA and CAA optimization problems are given as a flowchart in Figure 3.

5 RESULTS AND DISCUSSIONS

The method of parameter tuning for evolutionary algorithms is presented by Eiben and Smith (Eiben AE, Smit SK. 2011). The best control parameters of MFO are shown in table 1.

TABLE 1 MFO CONTROL PARAMETERS

5.1 Simulation results of LAA

Table 3 shows the initial values of SLL and HPBW for symmetrical LAAs having uniform excitation with λ/2 inter-element spacing. The current excitation amplitude weights obtained by using MFO algorithm for 16-element, 18-element, 20-element symmetrical LAA are shown in Table 4.

TABLE 2 The initial value of SLL, HPBW for uniformly excited and uniformly spaced linear antenna array

No. of elements	SLL(dB)	HPBW(deg)
12	-12.6133	13
16	-13.2483	9

TABLE 3 The current excitation amplitude weights (I_n) of symmetrical LAA using MFO algorithm

No. of elements	Current Excitation Weights	SLL(dB)	HPBW(deg)	FNBW(deg)
12	0.5317 0.4606 0.3974 1.0000 0.3820 0.3699	-27.9607	5	13
16	0.9695 0.9510 0.6974 0.6831 0.6775 0.6760 1.0000 0.6702	-33.9194	4	8

Table 3 shows that as the no of elements increased, SLL, HPBW, FNBW are decreased. The maximum SLL values achieved by using MFO algorithm for 12-elements and 16-elements symmetrical LAA are -25.4168 dB and -31.2912 dB, respectively. The HPBW of 12-elements and 16-elements symmetrical LAA achieved by using MFO algorithm are 5 and 4 degree, respectively.

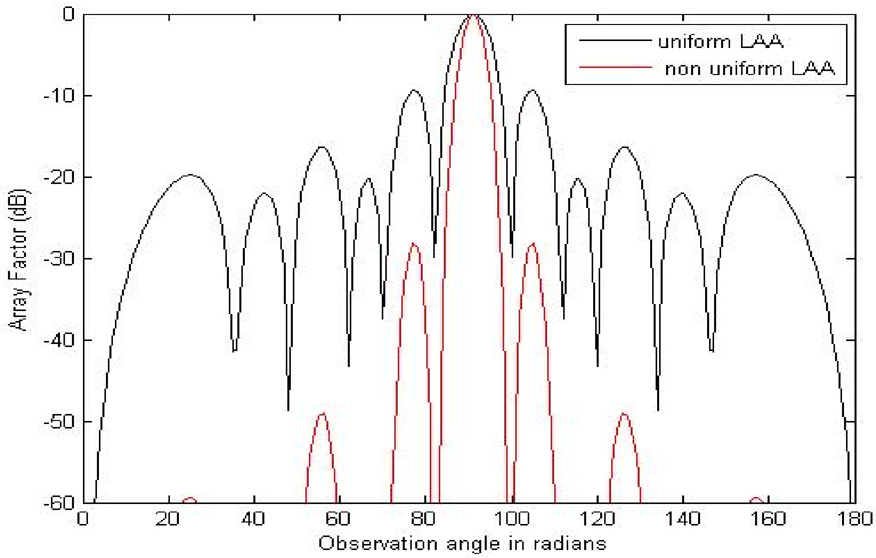

Fig 4: Radiation pattern of 12-element uniform and non-uniform LAA design.

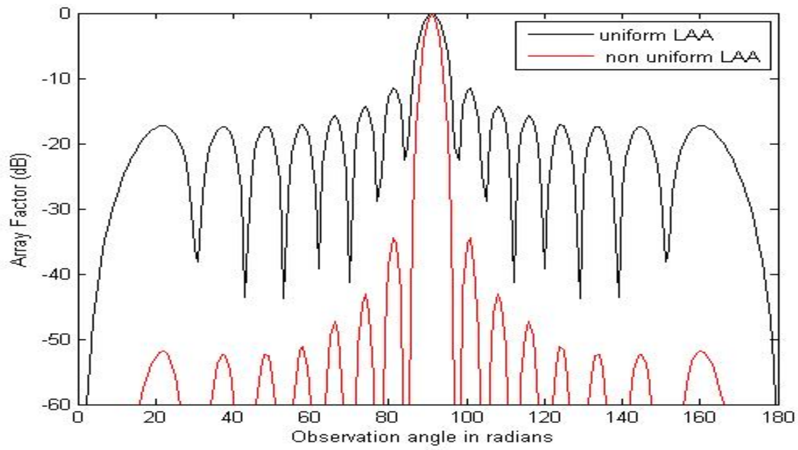

Fig 5: Radiation pattern of 16-element uniform and non-uniform LAA design.

5.2 Simulation results of non-uniform CAA

The current excitation weights and the inter-element spacing for 12-element, 14-element, 16-element non-uniform CAA design obtained by using MFO technique are shown in Table 7.Table 7 also contains SLL(dB) values, HPBW (deg) ,FNBW (deg) values are obtained by MFO algorithm when applied to optimize the 12-element, 14-element and 16-element CAA.

TABLE 4 The current excitation weights and inter element spacing of non uniform circular antenna arrays using MFO algorithm.

The results shows the SLL values of three different CAA structures of 12-element, 14-element and 16-element array are -21.14, -22.27, -23.56 dB, respectively.

No.of elements	Current Excitation Weights	Inter element Spacing	SLL (dB)	HPBW (deg)	FNBW (deg)
12	0.8612 0.7468 0.2581 0.5073 0.0031 0.1446 0.5194 0.4762 0.4963 0.1282 0.7163 0.7482	0.1750 1.9869 1.2144 0.8374 0.1522 1.3673 1.3903 0.8929 0.7153 0.1146 1.2714 1.0047	-21.14	4	10
14	0.5574 0.1696 0.2309 0.5749 0.4681 0.1518 0.1347 0.8429 0.3479 0.6760 0.2504 0.6426 0.0986 0.9525	1.4234 1.2735 1.5626 0.6440 0.9277 1.0742 0.9848 0.8372 0.2117 1.8010 0.5773 1.1537 1.0013 1.9585	-22.27	3	7
16	0.0649 0.7791 0.8397 0.8766 0.1061 0.5366 0.7821 0.0231 0.3380 0.9849 0.2616 0.8745 0.3882 0.3705 0.6788 0.8478	0.2621 0.3295 1.8647 0.5613 1.3470 0.2799 0.4790 0.7875 1.0031 0.8772 0.7267 1.5157 1.4665 1.4653 0.5299 1.4105	-23.56	2	4

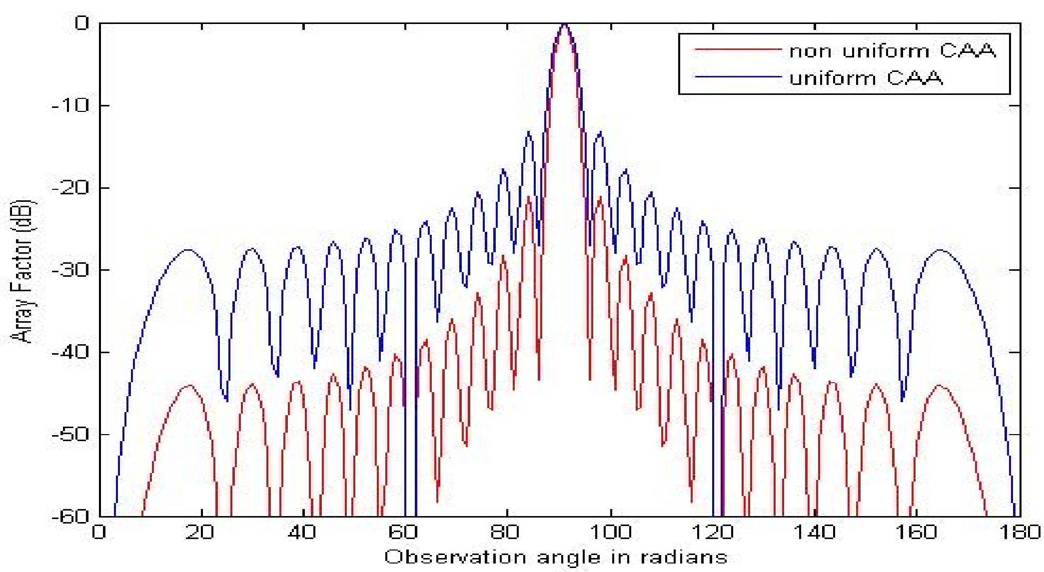

Fig 6 Radiation pattern of 12-element uniform and non uniform CAA design.

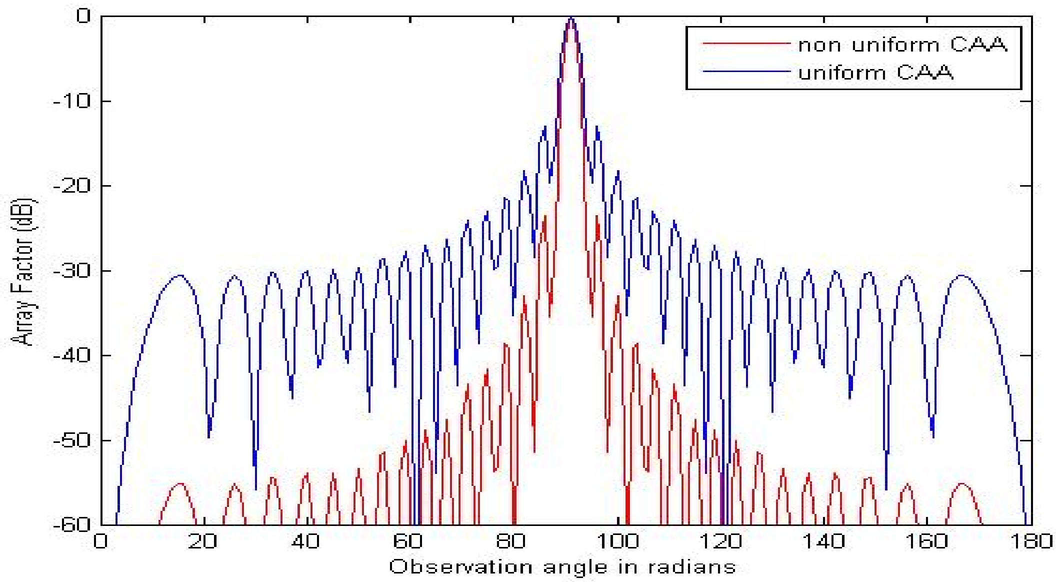

Fig 7: Radiation pattern of 14-element uniform and non-uniform CAA design.

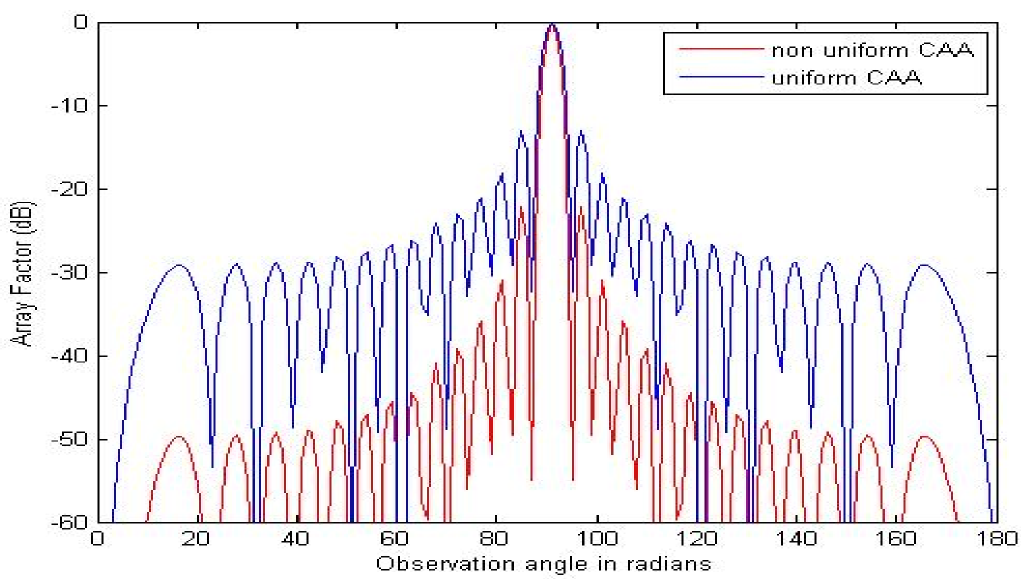

Fig 8: Radiation pattern of 16-element uniform and non-uniform CAA design.

6. CONCLUSIONS

This paper illustrates moth flame optimization for reduction of side lobe level(SLL) for symmetrical linear antenna array (LAA) and non-uniform single ring circular antenna array

(CAA) . By varying the number of elements, inter element spacing the reduced side lobe levels can be obtained. The results obtained by using MFO algorithm confirm an improved design in terms of suppressing the SLL and reducing HPBW and FNBW. The obtained results ensure that MFO algorithm has an excellent prospect to be used as an efficient optimizer for obtaining the optimal value of current excitation weights and the inter element spacing between the array elements for the synthesis and pattern modeling of a symmetrical linear antenna array and the non-uniform single ring circular antenna array.

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