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Design of Linear and Circular Antenna Arrays Using Cuckoo Optimization Algorithm

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Abstract—Cuckoo optimization Algorithm (COA) is employed for the optimization of linear and non-uniform circular antenna arrays. COA is a novel nature inspired computing algorithm which is motivated by the life of Cuckoo. Like other nature-inspired algorithms, COA is also a population-based method and uses a population of solutions to proceed to the global solution. The method of COA is used to determine a set of parameters of antenna elements that provide the required radiation pattern. The effectiveness of COA for the design of antenna arrays is shown by means of numerical results. Comparison of results of COA is made with that obtained using other popular methods. The results reveal the superior performance of COA as compared to other techniques both for design of linear and circular antenna arrays.

1. INTRODUCTION

Many applications, such as mobile communication and spatial detection techniques, require antennas that have large directivity, which cannot be achieved by a single antenna. For the large directivity, the assignment of antenna elements to a group with particular electrical and geometrical configurations is of interest. This configuration is considered as an array. Classical methods of designing antenna arrays are not effective as they often encounter local minima and are not able to find a global solution. This has led to the use of nature inspired methods for antenna array synthesis which provide an alternative to classical methods. Nature inspired methods are robust and able to provide global solutions. There are a number of different nature inspired methods that have been used for antenna array synthesis. Among them are genetic algorithms (GA) [1, 2], differential evolution (DE) [2–4], ant colony optimization (ACO) [5, 6], particle swarm optimization (PSO) [7–16], modified invasive weed optimization (MIWO) [17], firefly algorithm (FA) [18–20], biogeography based optimization (BBO) [21–24] and cuckoo search (CS) [25]. These methods perform better and provide more flexible results than the classical methods for antenna array synthesis.

Synthesis of linear antenna arrays has been extensively studied in the past years [1, 3–11, 14–16, 18, 23–27]. The common optimization goal of synthesis is the side lobe level (SLL) suppression (while preserving the main lobe gain) and the null control to reduce interference effects. The antenna synthesis methods achieve the desired pattern generally by controlling the complex weights (both amplitude and phase), amplitude only, phase only and array element positions only. Each of these methods has its merits and demerits, which have been discussed in [26].

Circular arrays have become popular in recent years over other array geometries because they have the capability to perform the scan in all directions without a considerable change in the beam pattern and provide 360° azimuth coverage. Moreover, circular arrays are less sensitive to mutual coupling as compared to linear and rectangular arrays since these do not have edge elements [28]. Circular arrays are used in air and space navigation, underground propagation, radar, sonar, and many other systems [28]. Hence the synthesis of the circular arrays is under active research by many groups. The GA [2], PSO [12], HDLPSO [13], and MIWO [17], FA [20] and BBO [22] techniques have been used

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for finding the element amplitudes and positions that provide a radiation pattern with maximal SLL reduction with a constraint of beam width.

COA is a population-based technique introduced in [29]. The COA is one of the several recent and powerful metaheuristics. The first algorithm which is based on lifestyles of cuckoos was developed by Yang and Deb and is known as 'Cuckoo Search' (CS) [30]. The CS algorithm is based on the obligate blood parasitic behavior of some cuckoo species in combination with the Levy flight behavior of some birds and fruit flies. The CS algorithm does not completely imitate the behavior of cuckoos. It has not taken into account the immigration behavior of Cuckoos. Rajabioun developed another algorithm based on cuckoo lifestyle, called "Cuckoo Optimization Algorithm" (COA) [29]. This algorithm inspires and models cuckoo life cycle much better and more precisely. He proved the efficiency of this algorithm via a benchmarking study. He showed that this algorithm has high speed of convergence and reaches the global solution easily. COA is superior than other nature inspired computing algorithms because of multiple functions of COA operators (including egg laying and immigration operators). Other optimization algorithms have the operators which are defined for one specific objective. The performance of COA on benchmark functions and its features tempted the authors to apply the algorithm to linear and circular antennas as to see how it performs for antenna problems.

The rest of the paper is organized as follows: Section 2 discusses the geometry and general design for the linear and circular antenna. In Section 3, the COA algorithm is explained. Section 4 presents design examples and the results and in Section 5 conclusions are presented.

2. ANTENNA ARRAY PATTERN FORMULATION

A $2N$-element distributed along x-axis with unequal inter-element amplitudes, phases and spacing is considered as given in Figure 1. The array factor (AF) may be written as [28]:

$$\mathrm{AF}(\phi) = \sum_{n=1}^{2N} I_n e^{(j[kx_n \cos(\phi)+\varphi])} \tag{1}$$

where k is the wave number, and I_n, ϕ_n, x_n are, respectively, the excitation amplitude, phase, and location of nth element.

An N-element circular array is shown in Figure 2. The elements are non-uniformly spaced on a circle of radius a in the x-y plane. The elements are assumed to have the same characteristics as

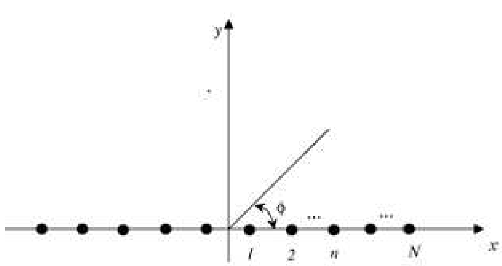

Figure 1. $2N$-element symmetric linear array along the x-axis.

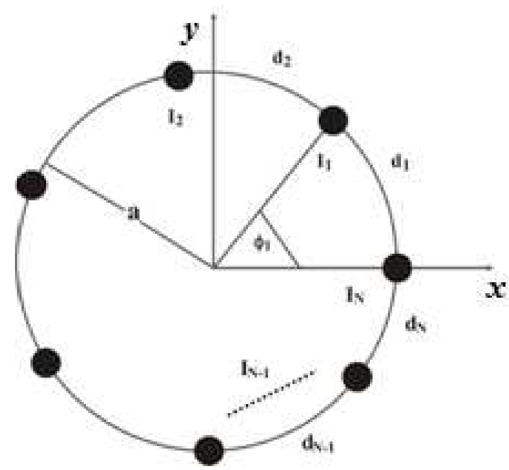

Figure 2. N-element circular array in x-y plane.

isotropic sources. The array factor of this array configuration is given by [28]

$$\mathrm{AF}(\theta) = \sum_{n=1}^{N} I_n e^{j(ka\cos(\theta-\phi_n)+\alpha_n)}, \tag{2}$$

$$k * a = 2\pi a/\lambda_w = \sum_{i=1}^{N} d_i, \tag{3}$$

where I_n and α_n denote the amplitude and the phase excitation of the nth element. d_n is the arc distance from element n to $n+1$ (arc longitude), $k = 2\,\pi/\lambda_w$ the wave number, θ the angle of incidence of a plane wave, and λ_w the wavelength of the signal. The angular position of nth element in x-y plane is given by:

$$\phi_n = (2\pi/ka)\sum_{i=1}^{n} d_i, \tag{4}$$

where ϕ_n is the angular position of the nth element in x-y plane. For directing the main beam towards θ_0 direction, the excitation phase of the nth element is given by

$$\alpha_n = -ka\cos\left(\theta_0 - \phi_n\right). \tag{5}$$

In this work, the direction of the main beam is along the x-axis, i.e., $\theta_0 = 0$.

3. CUCKOO OPTIMIZATION ALGORITHM

COA is a population-based evolutionary algorithm recently developed by Rajabioun in 2011 [29]. COA is inspired by the brood parasitism of some cuckoo species. Brood parasitism of cuckoos is laying their eggs in the nests of other host birds (of other species).

The steps involved in COA are as under:

i) Generate initial cuckoo habitat with some random points on the profit function.

The habitat of a cuckoo can be written as,

$$\text{Habitat} = [x_1, x_2, x_3, \ldots, x_{Nvar}] \tag{6}$$

Each of the variable values (x_1, x_2, x_3, ..., x_{Nvar}) is a real number. One habitat in COA is one solution and it is analogous to 'chromosome' in GA and 'position' in PSO.

In antenna array optimization, one habit corresponds to one candidate solution consisting of geometrical or electrical parameters of the antenna array.

ii) Dedicate some eggs to each cuckoo and initialize their Egg Laying Radius (ELR).

In an optimization problem with upper limit of x_{ub} and lower limit of x_{lb} for variables, each cuckoo has an egg laying radius (ELR) which is proportional to the total number of eggs, number of current cuckoo's eggs and also variable limits of x_{ub} and x_{lb}. So, ELR is defined as:

$$\text{ELR} = \alpha \times \frac{\text{Number of current cuckoo's eggs}}{\text{Total number of eggs}} \times (x_{ub} - x_{lb}) \tag{7}$$

where α is an integer, used to control the maximum value of ELR.

In context of antenna array optimization, limiting of ELR represents a way to limit the allowed ranges of variables in an antenna array.

iii) Let cuckoos to lay eggs inside their corresponding ELR.

Each cuckoo starts laying eggs randomly in some other bird's nests within her ELR. This egg laying process is analogous to generation of new children in GA and determination of new particle positions in PSO. In antenna array optimization problem, this corresponds to generation of new candidate solutions with random changes in variables depending upon ELR. After all the cuckoos have laid their eggs, some of them that are less similar to host bird's eggs are detected by host birds and thrown out of their nests. Those with least profit values are eliminated. The profit value of a habitat is given by,

$$\text{Profit} = f_p(\text{habitat}) = f_p(x_1, x_2, x_3, \ldots, x_{Nvar}) \tag{8}$$

This calculation of profit values corresponds to fitness or objective function of the antenna array. The formulation of fitness function of the antenna array has been described in the Section 4.
Now, let other eggs hatch up and chicks grow out of eggs. Another interesting feature about laid cuckoo eggs is that only one egg in a nest has the chance to grow. This is because when cuckoo egg hatches and the chicks come out, she throws the host bird's own eggs out of the nest. In case the host bird's eggs hatch earlier and cuckoo egg hatches later, cuckoo's chick eats most of the food host bird brings to the nest (because of her much bigger body, she pushes other chicks and eats more). After couple of days the host bird's own chicks die from hunger and only cuckoo chick remains in the nest.

iv) Evaluate the habitat of each newly grown cuckoo.
Based on the profit values, limit the maximum number of cuckoos to $N_{\max}$.

v) Cluster cuckoos and find best group and select good habitat for immigration of cuckoos.
When the time for egg laying of young cuckoos arrive they need to immigrate to new and better habitats with more similarity of eggs to host birds and also with more food for youngsters. After the cuckoo groups are formed in different areas, the society with best profit value is selected as the goal point for other cuckoos to immigrate.

vi) Check whether the terminating condition has been achieved.
This can be a fixed number of iterations that are allowed or when 95% of the cuckoos have converged to a single best habitat. If terminating condition has not been achieved, go to step 2. Otherwise, the process is terminated.

COA has been tested for five benchmark functions and found to converge faster than GA and PSO algorithms [29]. The main reason that makes COA work better than other nature inspired computing algorithms lies in multiple functions of COA operators (including egg laying and immigration operators). In all other optimization algorithms, the operators are defined for one specific objective. But in COA, defined operators do multiple functions simultaneously. For example, clustering helps cuckoos divide the search area into some parts and determine the best part approximately. This part hopefully is the one that global optimum point exists in. Then all the cuckoos immigrate toward that good area and search inside that area more precisely. This leads to faster convergence of COA.

3.1. Design Examples for Linear Array

In this work, two cases of linear array have been taken that have been investigated by number of researchers using different optimization methods. This is done to make a comparison of COA with popular evolutionary techniques that has been considered in the past for the same problem such as PSO [8], comprehensive learning particle swarm optimization (CLPSO) [10], chaotic particle swarm optimization (CPSO) [14] inheritance learning particle swarm optimization (ILPSO) [15] and CS [27]. Moreover, in this work, an attempt has been made to compare COA against other popular evolutionary techniques that have not been applied for this problem. Hence in this work, other methods like BBO, FA, and DE have also been applied for the optimization and their results have been compared with COA results.

The objective of linear antenna optimization is to suppress the maximum SLL (MSLL) and at the same time keeping the main lobe to a desired beamwidth within $\pm 1^\circ$ by finding the optimum element positions. This is done by combining the objectives in one fitness function and using penalty method as has been done in [10]. This design problem is therefore defined by the minimization of the fitness function using COA and is given by:

$$\text{Fitness} = \text{MSLL} + \alpha * \max\{0, |\text{FNBW} - \text{FNBW}_d| - 1\} + \alpha * \left\{ \sum\nolimits_{k=1}^{K} \max\{0, \text{AF}_{\text{dB}}(\phi_k) - C_{\text{dB}}\} \right\} \quad (9)$$

where MSLL is the maximum side lobe level, FNBW the calculated beamwidth, FNBW_d the desired beamwidth, K the number of the required null directions C_{dB} the desired null level in dB, ϕ_k the direction of the kth null, and α a very large number. In a penalty method, the feasible region is expanded but a large penalty or cost is added to the original fitness function if the solutions lie outside of the original feasible function. Hence, the value of α is taken very large so as to ensure that solutions not fulfilling the constraints have large fitness values. In this work, the FNBW is determined computationally from the radiation pattern data. The population size is taken as 40 as was done in case of CLPSO [10]. The number of generations was set equal to 2000. All the algorithms have been run for 20 times and their best results have been taken. The value of α in the fitness function is taken as 10^6.

In the first case, an antenna with 28 elements is optimized by varying the positions. The aim is to suppress MSLL and have nulls in directions of 120°, 122.5° and 125°. The desired null level is −60 dB. The desired beam width is 8.35°. The beam width tolerance was set to ±12%. The convergence plot of COA for this optimization along with the convergence of BBO, CS, DE, and FA is shown in Figure 3. It is evident from the convergence characteristics that speed of convergence of COA is higher as compared to BBO, CS, DE and FA. The optimized variables and the performance parameters are listed in Tables 1 and 2 respectively. As seen from the results in Table 2, the MSLL obtained by COA is −21.86 dB which is least among the other listed results of other algorithms. The nulls are also achieved in the required angular directions. The radiation pattern of the COA obtained array is shown in Figure 4. The radiation pattern of antenna arrays obtained from PSO [8], CLPSO [10] and FA optimization are also shown in Figure 4 for comparison.

In the second case, a 32-element antenna array is taken for optimization. The goal is to reduce the MSLL and have a null in the direction of 99°. The desired beam width is set to 7.1°. The beam width tolerance is set to ±14%. The convergence plot of COA for this optimization along with the convergence of BBO, DE, and FA is shown in Figure 5. Tables 3 and 4 give the geometry and performance values

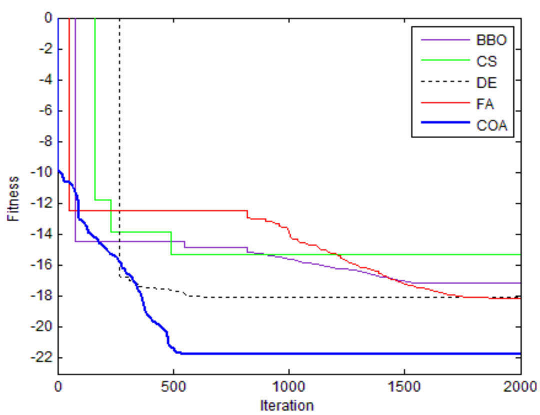

Figure 3. Convergence graph of different algorithms for 28-element linear antenna.

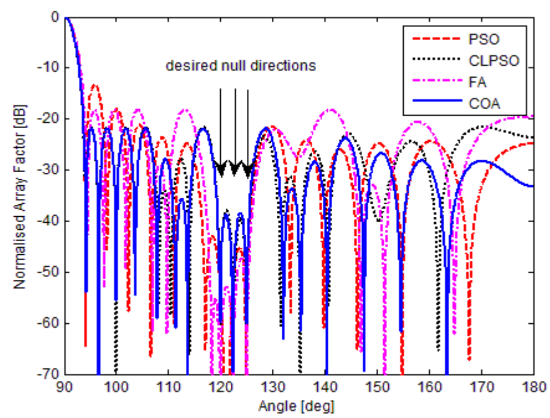

Figure 4. Radiation pattern for 28-element array for minimum MSLL and null at 120°, 122.5° and 125°.

Table 1. Geometry of the 28-element linear antenna array obtained using COA.

Element	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Position	0.4719	1.3622	2.3091	3.1064	4.0688	5.2663	6.2660
Element	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Position	7.0839	8.2914	9.6443	11.1218	12.7414	14.2912	14.2445

Table 2. The optimal results found by different algorithms for 28-element linear antenna array.

Algorithm	**PSO [8]**	**CLPSO [10]**	**FA**	**BBO**	**CS**	**DE**	**COA**
MSLL (dB)	−13.22	−21.60	−18.16	−17.13	−15.30	−18.05	**−21.86**
Null at 120° (dB)	−52.73	−60.45	**−88.58**	−63.66	−62.27	−60.14	−60.08
Null at 122.5° (dB)	−51.65	−60.00	**−68.82**	−64.68	−61.09	−60.00	−60.05
Null at 125° (dB)	−61.46	−60.61	−61.01	−61.36	**−63.98**	−60.08	−60.10

of different algorithms for 32-element antenna respectively. The MSLL obtained by COA is −23.81 dB which is lower than the obtained by PSO [8], CLPSO [10], CPSO [14], ILPSO [15] CS [27], FA, BBO and DE. The value of array factor in null direction is also least as compared to other algorithms. The radiation pattern of COA optimized linear antenna array is shown in Figure 6.

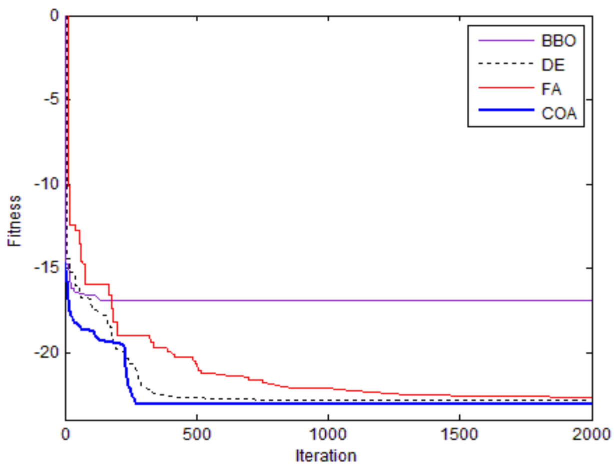

Figure 5. Convergence graph of different algorithms for 32-element linear antenna.

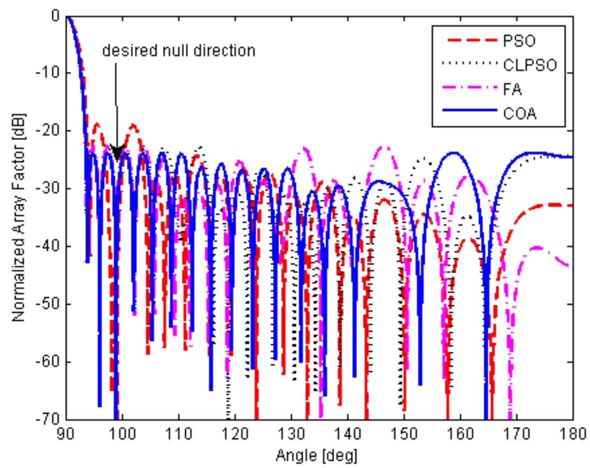

Figure 6. Radiation pattern for 32-element array for minimum MSLL and null at 99°.

Table 3. Geometry of the 32-element linear antenna array obtained using COA.

Element	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Position	0.4328	1.2397	2.1242	2.9799	3.8806	4.7725	5.6434	6.6828
Element	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Position	7.6270	8.7630	9.8809	11.1204	12.5260	14.2445	16.1763	17.6054

Table 4. The optimal results found by different algorithms for 32-element linear antenna array.

	PSO [8]	**CLPSO [10]**	**CPSO [14]**	**ILPSO [15]**	**FA**	**BBO**	**CS [27]**	**DE**	**COA**
MSLL (dB)	−18.80	−22.73	−23.17	−23.75	−22.64	−16.93	−22.8	−22.81	**−23.81**
Null at 99° (dB)	−62.12	−60	−63.16	−73	−60.59	−61.73	−62.63	−60.03	**−79.85**

3.2. Design Examples for Circular Antenna Array

In this section, the COA algorithm is applied to three non-uniform circular design problems that have already been dealt by using GA [2], HDLPSO [13] and MIWO [17]. The three instantiations are circular antenna arrays with 8, 10, and 12 elements.

The goal of the synthesis of the circular antenna in this work is to determine the electrical and geometrical structure of the circular antenna array for having the radiation pattern with the minimum SLL and narrower FNBW and at the same time keeping the circumference of antenna to a minimum. The minimum SLL means lowering both the average SLL (ASLL) and the maximum SLL (MSLL). Decreasing the MSLL for a specific FNBW helps in increasing the directivity. In the present world, emphasis are on miniaturization, hence it is also desired to minimize the circumference of the circular antenna arrays. The fitness function to achieve the desired circular antenna using COA is given by:

$$\text{Fitness} = a * F_{NU} + b * F_{\text{SLA}} + c * F_{\text{MSLL}} + d * F_D \tag{10}$$

$$F_{NU} = |\text{AF}(\phi_{nu1})| + |\text{AF}(\phi_{nu2})| \tag{11}$$

$$F_{\text{SLA}} = \frac{1}{\pi + \phi_{nu1}} \int_{-\pi}^{\phi_{nu1}} |\text{AF}(\phi)| d\phi + \frac{1}{\pi - \phi_{nu2}} \int_{\phi_{nu2}}^{\pi} |\text{AF}(\phi)| d\phi \tag{12}$$

$$F_{\text{MSLL}} = |\text{AF}(\phi_{ms1})| + |\text{AF}(\phi_{ms2})| \tag{13}$$

$$F_D = \sum\nolimits_{i=1}^{n} d_i \tag{14}$$

where ϕ_{nu1} and ϕ_{nu2} are the two angles at the null. ϕ_{ms1} is the angle where the maximum side lobe level is obtained in the lower band $[-\pi, \phi_{nu1}]$ and ϕ_{ms2} the angle where the maximum side lobe level is obtained in the lower band $[\phi_{nu2}, -\pi]$. In the above fitness function a, b, c, d are the weights assigned to the functions. The function F_{SLA} is responsible for minimizing the ASLL while F_{MSLL} is used to minimize the MSLL. F_{NU} is employed for having the desired FNBW and F_D is used to limit the circumference of the circular antenna array. Hence, the goal of the optimization problem is to search for the current amplitudes (I_n) and the arc distances between the elements (d_n) that minimize the above fitness function.

The values of the element amplitudes are allowed to vary between [0, 1] and the separations between $[0, \lambda_w]$ where λ_w is the wavelength of the signal. The COA algorithm is applied to three circular array antennas with $N = 8$, 10, and 12 elements. The main lobe is steered at $\theta_0 = 0$. All the experiments are run 20 times independently. The values of a, b, c, d are taken as 1.5, 3, 2 and 0.2 respectively. Since the results reported in [13, 17, 22] were only the best ones, the best results found by COA are used for comparisons.

In the first case the circular antenna array with $N = 8$ elements is optimized with COA. The number of parameters to be optimized are sixteen, i.e., eight current element excitations and eight element positions. The optimal performance parameters and the corresponding optimized variables are respectively listed in Tables 5 and 6. The corresponding radiation pattern of the optimal array is depicted in Figure 7. The MSLL and ASLL obtained by COA are -13.32 dB and -22.60 dB respectively. The circumference of COA optimized antenna is $4.40\lambda_w$ which is also smaller as compared to HDLPSO [13], MIWO [17], FA [20], BBO [22] and CS optimized antennas. The value of MSLL and ASLL for COA is also least among the various algorithms. Moreover, the directivity of COA optimized antenna is highest as compared to other algorithms and is listed in Table 5.

In the next example, the COA algorithm is employed to optimize a circular antenna array with $N = 10$ elements for the same objective and parameters. The constraints are the same as in the

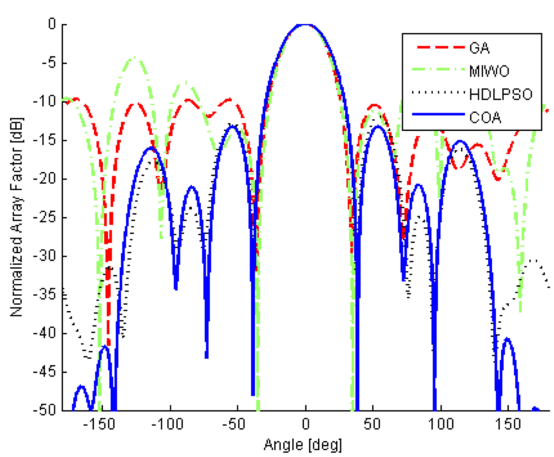

Figure 7. Radiation pattern for $N = 8$ elements.

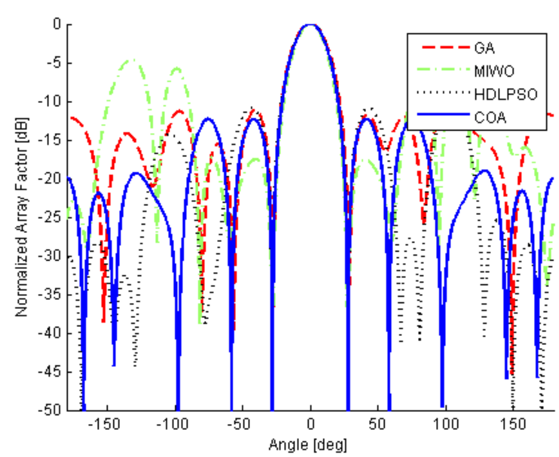

Figure 8. Radiation pattern for $N = 10$ elements.

Table 5. The optimal results found by different algorithms for circular antenna arrays.

N	Algorithm	MSLL (dB)	ASLL (dB)	$\sum \mathbf{d_i(\lambda_w)}$	Directivity (dB)
8	GA [2]	−9.81	−13.70	4.40	10.92
	MIWO [17]	−2.2780	−10.74	5.95535	12.338
	HDLPSO [13]	−12.04	−20.313	4.426	9.915
	FA [20]	−12.93	−15.48	4.65	11.86
	CS	−10.31	−17.09	4.4631	12.78
	BBO [22]	−9.8375	−15.9604	4.43	12.1800
	COA	**−13.32**	**−22.60**	**4.40**	**14.57**
10	GA [2]	−10.8643	−15.4358	6.0886	12.4630
	MIWO [17]	−4.6325	−13.7812	7.3234	11.7446
	HDLPSO [13]	−10.5447	−19.70	**5.8406**	11.19
	FA [20]	−13.21	−16.72	6.070	13.35
	CS	−10.6774	−17.0604	5.7897	13.4797
	BBO [24]	−11.6549	−17.7981	5.8764	13.8813
	COA	**−12.35**	**−19.77**	5.9075	**15.02**
12	GA [2]	−11.8589	−15.7807	7.7724	13.2370
	MIWO [17]	−5.1040	−14.26	7.9114	12.2683
	HDLPSO [13]	−7.2880	**−19.813**	7.2818	12.212
	FA [02]	−14.13	−17.886	7.21	14.54
	CS	−10.9227	−15.9043	7.11	13.3685
	BBO [22]	−14.37	−19.46	10.61	16.37
	COA	**−14.41**	−18.2	**7.11**	**14.60**

Table 6. The optimal variables obtained with COA.

N	$[\mathbf{d_1}, \mathbf{d_2}, \mathbf{d_3}, \ldots, \mathbf{d_n}]$ in $\boldsymbol{\lambda_w}$'s $[\mathbf{I_1}, \mathbf{I_2}, \mathbf{I_3}, \ldots, \mathbf{I_n}]$
8	[0.3204 0.6708 0.1472 0.7852 0.5890 0.8165 0.8022 0.3094]
	[0.7928 0.1399 0.4202 0.8471 0.8903 0.4587 0.8352 0.1638]
10	[0.3214 0.9695 0.3671 0.9672 0.3232 0.3194 0.9681 0.3662 0.9703 0.3233]
	[0.5113 0.2175 0.4678 0.4498 0.7571 0.7679 0.5367 0.5855 0.5126 0.6328]
12	[0.2455 0.8558 0.6575 0.6897 0.8595 0.3400 0.1807 0.8317 0.6493 0.7115 0.8168 0.2724]
	[0.9978 0.6237 0.5823 0.7456 0.9990 0.9961 0.5042 0.6460 0.6017 0.6818 0.9632 0.7271]

previous example. The best radiation pattern found by COA in Figure 8 has a MSLL of −12.35, ASLL of −19.77 dB and directivity of 15.02 dB. The optimal performance parameters and the corresponding optimized variables are respectively listed in Tables 4 and 5. These are again compared with the results obtained by the GA [2], HDLPSO [13], MIWO [17], FA [20], BBO [22] and CS. Again, the COA has outperformed the other algorithms in terms that it has got optimum value of MSLL, ASLL and circumference in contrast to other algorithms. For comparison, the radiation patterns of the antennas obtained by the GA [2], HDLPSO [13] and MIWO [17] techniques are also plotted in Figure 8. The radiation pattern clearly shows that COA achieves excellent results.

In the last example, the COA method is utilized to optimize a non-uniform circular array for $N = 12$ elements. The radiation pattern of the optimal array with COA is shown in Figure 9. The optimal performance parameters and the corresponding optimized variables are respectively listed in Tables 5 and 6. The corresponding array pattern in Figure 9 has a MSLL of −14.41 dB and ASLL of −18.2 dB. As shown in Table 5, the optimal MSLL by COA is 2.56 dB, 7.12 dB, 9.31 dB, 0.28 dB,

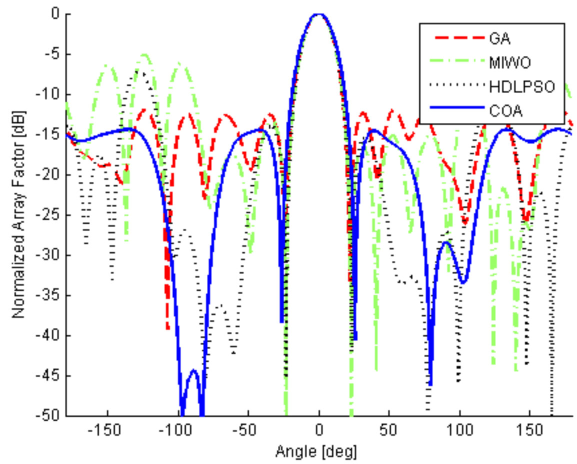

Figure 9. Radiation pattern for $N = 12$ elements.

0.04 dB and 2.6 dB lower than MSLL of the best array in GA [2], HDLPSO [13], MIWO [17], FA [20], BBO [22] and CS, respectively. Though the ASLL obtained by BBO [22] is better than obtained by COA but the aperture of BBO antenna is very large and hence COA optimized antenna is better than BBO.

4. CONCLUSIONS

This paper illustrated the use of COA algorithm in the pattern synthesis of antenna arrays. COA is a new optimization algorithm which is inspired by lifestyle of a bird called Cuckoo. Special characteristics of cuckoos in egg laying and breeding had been the basic motivation for development of this new optimization algorithm. The COA method efficiently computes the design of several antenna arrays to generate a radiation pattern with desired properties. In the first part of the paper, linear arrays are dealt with. The aim of optimization was to minimize the maximum SLL and controlling nulls by adjusting the elements positions. The numerical results show that the COA method produces minimum SLL compared with the array obtained using CLPSO, CPSO, PSO, ILPSO, FA, BBO, DE and CS algorithms. The COA method is also employed to optimize elements locations and excitations amplitude of circular arrays. The results found show that the maximum SLL obtained is lower than the GA, MIWO HDLPSO FA, CS and BBO optimized antenna arrays.

In this work, COA has emerged as an attractive alternative to more admired algorithms such as the GA, PSO and DE. This work of antenna optimization by the COA method was mainly inspired by the popularity of these algorithms for solving electromagnetic optimization problems. For a new algorithm to emerge, it is imperative to perform proper comparison with the already accepted traditional methods. It is found that COA has been able to provide good solutions at a faster convergence speed. The main advantage of COA is its simplicity and ease of implementation. It is hoped that COA due its simplicity, faster convergence speed and ability to provide high-quality solutions will emerge as a powerful tool for not only for electromagnetics community but for other researchers in dealing with optimization problems.

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