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Design of non-uniform circular antenna arrays using biogeography-based optimisation

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Abstract: Biogeography-based optimisation (BBO) is employed for the optimisation of non-uniform circular antenna arrays. In BBO, the problem solutions are represented as islands and the sharing of features between solutions corresponds to immigration and emigration between the islands. The scheme of BBO is employed to find out an optimal set of weights and antenna element separations to provide a radiation pattern with maximum side lobe level (SLL) reduction with the constraint of a fixed major lobe beam width. The capability of BBO is demonstrated by taking different sizes of antennas. The results show that the design of non-uniform circular antenna arrays using the BBO algorithm offers a SLL reduction better than that obtained using genetic algorithms, particle swarm optimisation and simulated annealing.

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 an array. Antenna arrays are of different types and shapes, such as linear, rectangular, circular and hexagonal, and have been applied to radar and sonar. The design of antenna arrays is difficult since the objective function and constraint conditions are often highly non-linear and non-differentiable [1]. Poor design may result in a polluted electromagnetic environment. This will also result in wastage of power, which is a vital aspect in wireless devices that run on batteries. 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 evolutionary methods for antenna array synthesis which provide an alternative to classical methods. Evolutionary methods are robust and able to provide global solutions. There are a number of different evolutionary methods that have been used for antenna array synthesis. Among them are genetic algorithms (GA) [2–4], ant colony optimisation [5–7], particle swarm optimisation (PSO) [8–12], simulated annealing (SA) [13–15] and the bees algorithm [16]. These methods perform better and provide more flexible results than the classical methods for antenna array synthesis.

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 [17]. Circular arrays are used in air and space navigation, underground propagation, radar, sonar and many other systems [17]. Hence the synthesis of the circular arrays is under active research by many groups. The GA [4], PSO [9] and SA techniques [15] have been used for finding the element amplitudes and positions that provide a radiation pattern with maximal side lobe level (SLL) reduction with a constraint of beam width. The results achieved by SA are better than those from the GA and PSO methods, but the computation time is longer. In [10], PSO is employed for circular arrays. Along with amplitudes and positions, the optimised phases of elements have been obtained. In [11], PSO was used for an 18-element planar uniform circular array (PUCA) with a phase-only control approach to synthesise a beam pattern. The crossed PSO algorithm has also been applied to synthesise a PUCA of 19 elements with centre-fed elements using a complex weight control strategy [12].

In this paper, biogeography-based optimisation (BBO) is applied to the optimisation of non-uniform circular arrays. BBO is a population-based evolutionary technique introduced in [18]. It has been applied for the design of linear antenna arrays for obtaining the maximum SLL reduction and null placement in desired directions in [19]. In [10], PSO was applied for linear and circular arrays but in this work only circular arrays are optimised for BBO whereas linear arrays have been optimised in [19]. Results obtained using BBO for the linear array are encouraging and better than those obtained using PSO [10]. The BBO method produced a lower value of SLL and better null placement as compared to PSO [10]. BBO method has been also applied in other areas, such as the power flow problem [20], optimisation of gear trains [21] and satellite image classification problems [22]. The aim of this paper is to present the optimisation of non-uniform circular antenna arrays using BBO for reducing the maximum SLL and at the same time keeping the beam width as small as possible. To the best of our knowledge, BBO has not been applied for the optimisation of the circular arrays before. It is well known in general that if the SLL is reduced, the beam width is increased [17]. Therefore the aim of the optimisation in this paper is to minimise the SLL while maintaining minimum possible beam width.

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

2 Circular antenna design

The N-element circular array is shown in Fig. 1. 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 isotropic sources. The array factor of this array configuration is given by [17]

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

$$k * a = 2\pi a/\lambda_{\mathrm{w}} = \sum_{i=1}^{N} d_i \tag{2}$$

where I_n, 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), $k = 2\pi/\lambda_{\mathrm{w}}$ is the wave number, θ is the angle of incidence of a plane wave and λ_{w} is the wavelength of the signal. The angular position of nth element in $x-y$ plane is given by

$$\phi_n = (2\pi/ka)\sum_{i=1}^{n} d_i \tag{3}$$

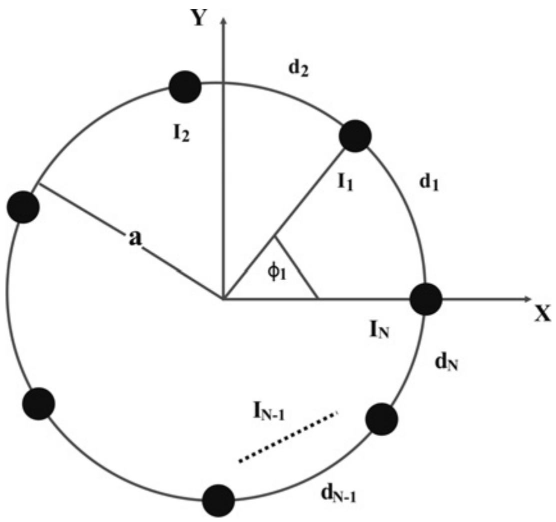

Fig. 1 *Geometry of N-element circular array*

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

$$\alpha_n = -ka\cos(\theta_0 - \phi_n) \tag{4}$$

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

3 Biogeography-based optimisation

BBO is a recently developed population-based evolutionary algorithm based on the theory of biogeography. Biogeography is the study of the distribution of the species in nature. The species migrate to different islands for their survival and better living conditions. BBO imitates this migration phenomenon for solving real-world optimisation problems. In common with the GA, the PSO and many other algorithms, BBO is motivated by natural phenomenon. In terms of biogeography, an island is defined as any ecological area which is geographically isolated from other islands. Each island has its measure of goodness for living which is known as the suitability index (SI). Islands that are well suited for living have a high SI. The SI of an island depends upon a number of factors, such as rainfall, temperature, diversity of species, population of the species and security. These factors are known as suitability index variables (SIV). The islands with a high SI have a large population as they are fit for living whereas the islands with low SI are not apt or friendly for living and have a thin population. High SI islands have a low immigration rate λ and high emigration rate μ simply because they are highly populated and cannot easily support new species. For the same reason, low SI islands have a high immigration rate λ and low emigration rate μ which allows more species to move into these islands. The islands with a high SI have many species that emigrate to nearby islands. The high SI islands are less dynamic than the low SI islands. Immigration to the low SI islands may raise its SI but if it is not improved, the island may become extinct. For many applications, it is sufficient to assume a linear correlation between the SI of an island and its immigration and emigration rates and that these rates are the same for all islands under consideration. The immigration and emigration rates depend on a number of species in the islands. These relationships are shown in Fig. 2.

Mathematically, the concept of migration between islands can be represented by a probabilistic model. Now, let P_s be probability that the island contains exactly S species at time

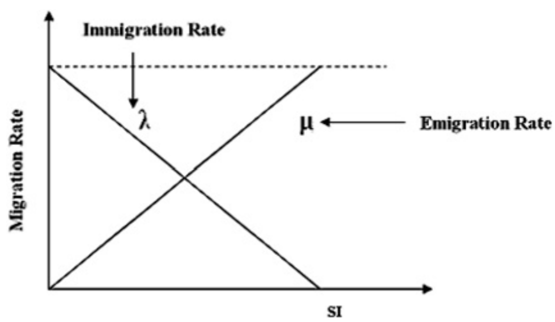

Fig. 2 *Island migration rate against island suitability index*

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t. P_s changes from time t to time $t + \Delta t$ as

$$P_s(t + \Delta t) = P_s(t)(1 - \lambda_s \Delta t - \mu_s \Delta t) + P_{s-1}\lambda_{s-1}\Delta t + P_{s+1}\mu_{s+1}\Delta t \tag{5}$$

where λ_s and μ_s are the immigration and emigration rates when there are S species in the island. This equation holds because in order to have S species at time $(t + \Delta t)$ one of the following conditions must exist:

1. there were S species at time t, and no immigration or emigration occurred between t and $t + \Delta t$;
2. there were $(S - 1)$ species at time t, and only one species immigrated;
3. there were $(S + 1)$ species at time t, and only one species emigrated.

If time Δt is small enough so that the probability of more than one immigration or emigration can be ignored, then taking the limit of (5) as $\Delta t \to 0$ gives

$$\dot{P}_S = \begin{cases} -(\lambda_s + \mu_s)P_s + \mu_{s+1}P_{s+1}, & S = 0 \\ -(\lambda_s + \mu_s)P_s + \lambda_{s-1}P_{s-1} \\ \quad + \mu_{s+1}P_{s+1}, & 1 \le S < S_{\max} - 1 \\ -(\lambda_s + \mu_s)P_s + \lambda_{s-1}P_{s-1}, & S = S_{\max} \end{cases} \tag{6}$$

For the straight line curves shown in Fig. 2, the values of the emigration and immigration rates are given by

$$\lambda_k = I_b\left(1 - \frac{k}{n}\right) \tag{7}$$

$$\mu_k = \frac{E_b k}{n} \tag{8}$$

where I_b is the maximum possible immigration rate, E_b is the maximum possible emigration rate, k is the number of species of the kth individual and n is the maximum number of species.

When $E_b = I_b$, combining (7) and (8) gives

$$\lambda_k + \mu_k = E_b \tag{9}$$

BBO technique imitates nature's way of distributing species, and is analogous to general problem solving. In BBO, for an N_{var}-dimensional optimisation problem, an island is a $1 \times N_{\text{var}}$ array. The population consists of $N_{\text{pop}} = n$ parameter vectors or islands, where N_{pop} is the total number of islands. Islands consist of solution features named SIV, corresponding to GA genes. A good solution is equivalent to the high SI island whereas a poor solution is given by the low SI island. The value of the SI of an island in BBO is similar to the fitness of solution in the other optimisation algorithms. The variable values or SIVs in an island are represented as floating numbers. The set of all such vectors is the search space from which the optimum solutions are to be found. The value of the SI is found by evaluating the cost of function at the variables $[\text{SIV}_{1,\ldots,}\ \text{SIV}_{N\ \text{var}}]$. Therefore we have

$$\text{SI} = f(\text{Island}) = f(\text{SIV}_1, \ldots, \text{SIV}_{N_{\text{Var}}}) \tag{10}$$

where f(Island) represents the value of cost or objective function. These solutions are made to share features among themselves by applying a migration operator. Each solution is modified depending on the probability P_{mod} which is a user-defined parameter. For each SIV, in each solution, it is decided probabilistically whether or not to immigrate. If the immigration is selected for a given solution feature, the emigrating island is selected for a given solution probabilistically using a roulette wheel normalised by μ. Similar to other population-based optimisation algorithms, elitism is introduced in the BBO to prevent the best p solutions from being corrupted by the migration operation. For this, p best solutions are kept aside from the migration operation by setting their immigration rate λ equal to zero and therefore these are retained in the population from one generation to the next.

The SI of an island can change suddenly because of some cataclysmic events owing to which the species count in an island changes rapidly from its equilibrium value. Therefore these random events can result in an abrupt change in the SI of an island. This is modelled in the BBO as SIV mutation. The species count probabilities are used to determine the mutation rate. The probabilities of each species count are determined by the differential equation in (6). Every population member has an associated probability, which represents the chances that exist as a solution for a given problem. For a solution S having a low probability P_s, its chances to mutate to some other solution are high. In the same way, if the probability of a solution is high, it has less chance to mutate to a different solution. Therefore very high and very low SI solutions have less likelihood to create a better SIV in the later stage. On the other hand, solutions with medium SI have a better chance to give much better solutions after mutation. This can be realised as a mutation rate which is inversely proportional to solution probability and is given by

$$m_s = m_{\max}\left(1 - \frac{P_s}{P_{\max}}\right) \tag{11}$$

```
for i= 1 to NP do
   Select I_i with probability based on λ_i
   if I_i is selected then
      for j=1 to NP do
         Select I_j with probability based on μ_j
         if I_j is selected
            Randomly select a SIV from I_j
            Replace a random SIV in I_i with selected SIV of I_j
         end if
      end for
   end if
end for
```

Fig. 3 *Algorithm for migration process of the BBO*

```
for i=1 to NP
   for j=1 to N_var do
      Use λ_i and μ_i to compute the probability Pi using (6)
      Select a SIV I_i (j) with probability based on P_i
      if I_i (j) selected then
         Replace I_i (j) with a randomly generated SIV
      end if
   end for
end for
```

Fig. 4 *Algorithm for mutation process of the BBO*

Table 1 Comparison of results obtained by BBO with other algorithms for $N = 8$ elements

PSO [9]	I_n	0.7765, 0.3928, 0.6069, 0.8446, 1.0000, 0.7015, 0.9321, 0.3583	SLL = −10.7996, 3 dB BW = 32
	d/λ_w	0.3590, 0.5756, 0.2494, 0.7638, 0.6025, 0.8311, 0.7809, 0.3308	
GA [4]	I_n	0.3289, 0.2537, 0.7849, 1.0000, 0.9171, 0.5183, 0.6176, 0.4612	SLL = −9.811, 3 dB BW = 32
	d/λ_w	0.1739, 0.3144, 0.6620, 0.7425, 0.6297, 0.8929, 0.4633, 0.5267	
SA [15]	I_n	0.3047, 0.4840, 0.7751, 0.9867, 0.3371, 0.4422, 0.4067, 0.6807	SLL = −12.00, 3 dB BW = 26.60
	d/λ_w	0.9997, 0.7743, 0.9042, 0.5652, 0.8056, 0.7818, 0.5848, 0.4594	
BBO	I_n	1.0000, 0.6736, 0.1678, 1.0000, 0.9088, 0.6553, 0.7571, 1.0000	SLL = −12.24, 3 dB BW = 18.6
	d/λ_w	0.6341, 1.0000, 1.8892, 0.8456, 0.5693 1.1639, 1.3329, 1.6367	

where m_{max} is a user-defined parameter and P_s is a function of S. This mutation scheme is likely to increase the diversity of the population. Without this variation, the highly probable solutions will have a tendency to be more dominant in the population. This mutation operation makes both low and high SI solutions likely to mutate, which gives a chance of improving both types of solutions in comparison to their earlier value. Elitism is introduced so that the best solutions are retained in the population. Elitism helps in reverting back to an old solution (solution before mutation) if a solution is ruined by the mutation process [18]. The migration and mutation operations are shown in Figs. 3 and 4.

The migration of the species among a set of neighbouring islands, combined with the mutation of the individual species, will have a propensity over several generations to generate the islands that draw and maintain large numbers of species in the course of immigration. Islands with low SI lose species through the extinction or emigration and will sometimes become uninhabited. The BBO algorithm emulates this behaviour in a manner that causes an 'optimal' island to come out from the original population of islands.

4 Design examples

In this section, the proposed BBO algorithm is applied to the three non-uniform circular antenna arrays with different numbers of elements. The goal of the synthesis of the 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 beam width. This is done by manipulating the excitation currents and the positions of the elements. The objective function to achieve the desired pattern using BBO is given by

$$F = w_1 |\mathrm{AF}(\theta_{\mathrm{msl}})| / |\mathrm{AF}(\theta_0)| + w_2\, \mathrm{BW} \qquad (12)$$

where w_1 and w_2 are the weighting coefficients, θ_0 is the direction of the main beam in $\theta \in [-\pi, \pi]$, $\mathrm{AF}(\theta_{\mathrm{msl}})$ is the value of the array factor where the maximum side lobe is attained at θ_{msl}, $\mathrm{AF}(\theta_0)$ is the array factor in the direction of the main beam at θ_0 and BW is the beam width of the array pattern measured in degrees. In this work, the beam width is determined computationally from the radiation pattern data. The optimisation problem can be summarised as the minimisation of function F to obtain a set of element amplitudes $[I_1, I_2, \ldots, I_N]$ and the separations among the elements $[d_1, d_2, \ldots, d_N]$. The values of the element amplitudes are allowed to vary between [0, 1] and the separations between $[0, 2\lambda_w]$, where λ_w is the wavelength of the signal. The BBO algorithm is applied to three circular array antennas with $N = 8$, 10 and 12 elements. The main lobe is steered at $\theta_0 = 0$. After many runs of the optimisation, the following parameters that yield satisfactory results are chosen for the BBO algorithm as follows:

- number of islands or population, $N_{\mathrm{pop}} = 100$;
- iterations or generations = 80;
- island modification probability = 1;
- mutation probability, $m_{max} = 0.005$;
- elitism parameter $p = 2$;
- maximum migration rates $E_b = 1$ and $I_b = 1$;
- $w_1 = 70$ and $w_2 = 1$.

In the first case, the circular antenna array with $N = 8$ elements is optimised with BBO. The number of parameters to be optimised are 16 that is eight current element excitations and eight element positions. The number of islands is equal to the population size and it is taken as 100. Each island consists of 16 SIVs made up of eight element amplitudes and eight separations between the elements, that is

$$X = (I_1, I_2, \ldots, I_8, d_1, d_2, \ldots, d_8) \qquad (13)$$

The BBO algorithm is applied to the circular antenna problem which consists of migration operator followed by mutation. The duplicate solutions are removed at each generation and restored with random mutations. The elitism operation is applied for preserving two fittest islands from each generation. The stopping criterion for BBO is the maximum number of generations as was the case in the PSO [9] and the SA methods [15]. The BBO method took around 7 min to complete this optimisation on a computer with a Pentium Core 2 Duo and 1 GB of RAM. The results obtained for this optimisation are given in Table 1. Along with the BBO results, the optimised excitations and positions of elements

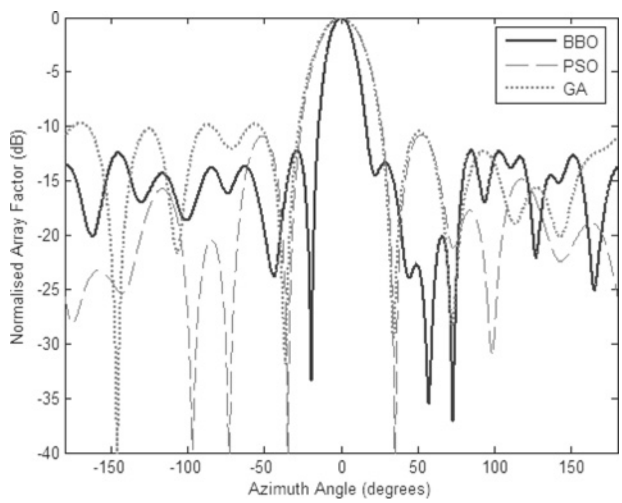

Fig. 5 *Radiation pattern for N = 8 elements using BBO results as compared to the results of the GA [4] and the PSO methods [9]*

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Table 2 Comparison of results obtained by BBO with other algorithms for $N = 10$ elements

PSO [9]	I_n	1.0000, 0.7529, 0.7519, 1.0000, 0.5062, 1.0000, 0.7501, 0.7524, 1.0000, 0.5067	SLL = −12.307 dB, 3 dB BW = 24.34°
	d/λ_w	0.3170, 0.9654, 0.3859, 0.9654, 0.3185, 0.3164, 0.9657, 0.3862, 0.9650, 0.3174	
GA [4]	I_n	0.9545, 0.4283, 0.3392, 0.9074, 0.8086, 0.4533, 0.5634, 0.6015, 0.7045, 0.5948	SLL = −9.811 dB, 3 dB BW = 32°
	d/λ_w	0.3641, 0.4512, 0.2750, 1.6373, 0.6902, 0.9415, 0.4657, 0.2898, 0.6456, 0.3282	
SA [15]	I_n	0.6920, 0.5679, 0.5937, 0.6703, 0.9693, 0.6014, 0.3575, 0.3020, 0.5908, 0.9718	SLL = −13.00 dB, 3 dB BW = 18.40^0
	d/λ_w	0.6221, 0.9880, 0.7777, 0.9934, 0.6217, 0.9514, 0.7626, 0.5980, 0.7655, 0.9410	
BBO	I_n	1.0000, 1.0000, 1.0000, 0.3819, 0.8970 1.0000, 0.7679, 0.8899, 0.7246, 1.0000	SLL = −13.95 dB, 3 dB BW = 16.60°
	d/λ_w	0.5301, 1.0603, 1.3264, 1.0000, 0.4307 0.4408, 1.5276, 1.3255, 1.0000, 0.5904	

obtained using a GA [4], PSO [9] and SA [15] are also listed for comparison. The maximum SLL obtained by BBO is −12.24 dB and the beam width is 18.6°. Evidently, BBO provides better SLL and beam width than other techniques. The SLL given by BBO is better by −1.5, −2.44 and 0.24 dB than those by the PSO, the GA and the SA optimised arrays, respectively. The obtained beam width is also narrower by 13.4, 13.4, and 8° than the PSO, the GA and the SA algorithms, respectively. The radiation pattern of the array obtained by BBO is plotted in Fig. 5 along with the radiation patterns of the GA and the PSO methods.

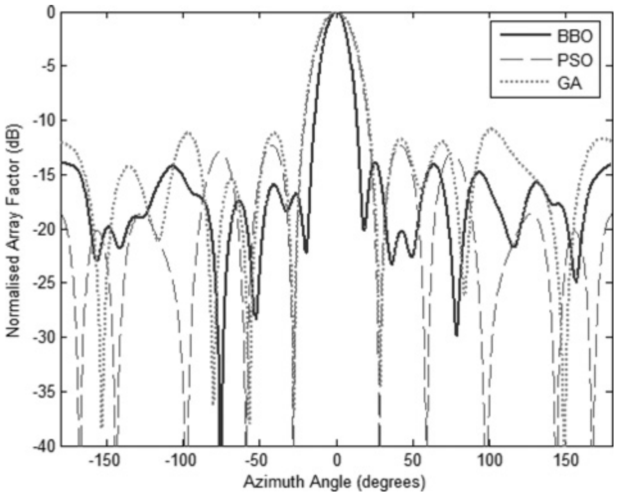

Fig. 6 *Radiation pattern for N = 10 elements using BBO results as compared to the results of the GA [4] and the PSO methods [9]*

In the next example, the BBO algorithm is employed to optimise a circular antenna array with $N = 10$ elements for the same objective and parameters. The constraints are also the same as in the previous example. The results obtained are listed in Table 2. These are again compared with the results obtained by the GA [4], the PSO [9] and the SA methods [15]. Again, the BBO outperforms the other algorithms. The obtained maximum SLL is better by −4.1, −1.65 and −0.95 dB than those achieved by the GA, the PSO and the SA methods, respectively. Moreover, the beam width obtained by the BBO is smaller by 16, 8 and 2.2° than those by the GA, the PSO and the SA methods, respectively. The optimised radiation pattern of the BBO array for this case is plotted in Fig. 6. For comparison, the radiation patterns of the antennas obtained by the GA and the PSO technique are also plotted in Fig. 6. The radiation pattern clearly shows that BBO achieves excellent results.

In the last example, the BBO method is utilised to optimise a non-uniform circular array for $N = 12$ elements. The results achieved after optimisation are shown in Table 3. Once again, the BBO technique yields results that are superior to the other algorithms. The maximum SLL is lower than those attained by the other algorithms. The improvement in the SLL is significant and it is lower by 2.54, 0.7 and 0.46 dB than those from the optimised antennas by the GA [4], PSO [9] and SA techniques [15], respectively. The obtained beam width is also better than those accomplished by the GA, the PSO and the SA techniques. It is narrower by 6, 7 and 5.2° as compared to PSO, the GA and SA, respectively. The radiation patterns for the antennas obtained by BBO, the GA and PSO are plotted in Fig. 7. Certainly, BBO again outperforms the other techniques in obtaining the required antennas.

Table 3 Comparison of results obtained by BBO with other algorithms for $N = 12$ elements

PSO [9]	I_n	0.9554, 0.6441, 0.7109, 0.7769, 1.0000, 1.0000, 0.3958, 0.7162, 0.6746, 0.7695, 0.9398, 0.6145	SLL = −13.670 dB, 3 dB BW = 21.2°
	d/λ_w	0.2569, 0.8509, 0.6607, 0.7057, 0.8540, 0.3734, 0.1609, 0.8321, 0.6464, 0.7079, 0.8330, 0.2682	
GA [4]	I_n	0.2064, 0.5416, 0.2246, 0.6486, 0.7212, 0.7913, 0.5277, 0.3495, 0.5125, 0.4475, 0.5233, 0.8553	SLL = −11.83 dB, 3 dB BW = 20.80°
	d/λ_w	0.4936, 0.4184, 1.4474, 0.7577, .4204, 0.5784, 0.4520, 0.8872, 0.7514, .4202, 0.4223, 0.7234	
SA [15]	I_n	0.6231, 0.3990, 0.3418, 0.6054, 0.9444, 0.7380, 0.6741, .03001, 0.4311, 0.5435, 0.4195, 0.9795	SLL = −13.91 dB, 3 dB BW = 19.60°
	d/λ_w	0.8315, 0.7910, 0.6699, 0.8087, 0.7347, 0.5331, 0.4777, 0.8960, 0.4874, 0.8657, 0.3461, 0.5105	
BBO	I_n	1.0000, 0.6501, 0.6224, 0.5020, 0.5540, 1.0000, 0.6683, 0.7234, 0.4410, 0.5123, 0.4793, 1.000	SLL = −14.372 dB, 3 dB BW = 14.80°
	d/λ_w	0.6704, 1.0000, 1.3046, 0.8081, 1.0000, 0.4031, 0.6183, 1.1574, 1.3465, 0.6551, 1.0000, 0.6539	

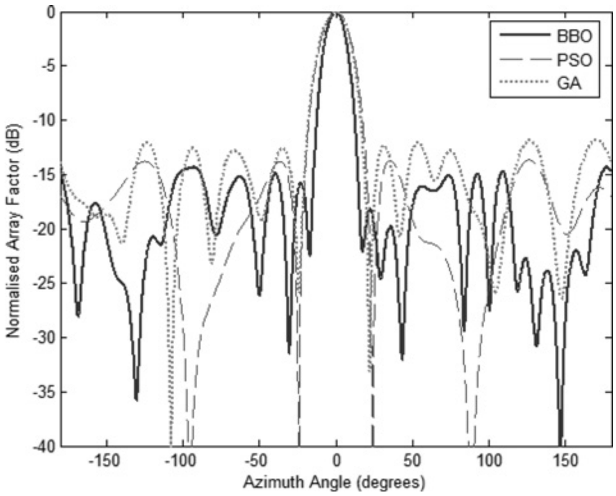

Fig. 7 *Radiation pattern for $N = 12$ elements using BBO results as compared to the results of the GA [4] and the PSO methods [9]*

5 Conclusions

In this paper, the BBO technique is applied to achieve the radiation pattern with the maximal SLL reduction with the constraint on the beam width of the non-uniform circular antenna array. BBO achieves this objective by varying the positions and the excitation amplitudes of elements. BBO is successful in obtaining circular arrays with lower SLL and narrower beam width than the circular arrays of previous published results using the GA, the PSO and the SA methods. The maximum improvement using BBO is 42.2% in terms of SLL reduction and is 50% in terms of the beam width as compared to a GA for $N = 10$ elements. As compared to the GA method, the main benefit of the BBO is its simplicity that provides an easy, quick and efficient resolution of medium and large problems. The number of iterations in BBO is quite less than SA and therefore it is faster than SA. It is also consistent in giving good-quality results. The BBO method has proved to be an efficient algorithm for the antenna optimisation problems.

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